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SHORT COMMUNICATION

Local pixel statistics based impulse detection and hybrid color filtering for restoration of digital color images

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ABSTRACT

This paper presents a two stage filtering system to remove random valued impulse noise from color images based on local statistics of the filtering window under consideration. In the first stage, to detect the noisy pixel, the locally adaptive threshold is derived from the pixels of the filtering window. In the second stage, the restoration of the noisy pixel is done on the basis of brightness and chromaticity information obtained from the neighbouring pixels in the filtering window. Simulation results show that the proposed scheme yields much superior performance in comparison with other color image filtering methods.

1. Introduction

Digital images are usually corrupted during their acquisition or transmission process. Several filtering methods have been proposed for the removal of impulse noise from color images using different approaches [1,2]. Most of these techniques use vector processing approach as it is widely accepted that this approach is more appropriate than the component-wise filtering approach, which can generate color artefacts in the filtered image. The vector median filter (VMF) [3], vector directional filter (VDF) [4] and the directional distance filter (DDF) [5] are the most commonly used vector filters for noise removal in color images. The main drawback of applying the component-wise approach for filtering is that the inherent correlation existing among pixels of different channels may be lost, resulting into color artefacts.

Often, the filtering operation is preceded by an impulse detection stage separately which ensures that only the noisy pixels are filtered. This prevents the blurring which is caused by the filtering of noise-free pixels. Indeed, some of the recent methods such as high performance detection (HPD) [6], directional weighted median filter (DWM) [7], and switching vector median filter based on CIELAB color space [8] are based on separate impulse detection scheme. Filtering of only noisy pixels results into better preservation of detail features. Most of the impulse detection methods available in the literature require a threshold value to make a decision whether the pixel under consideration is noisy or not. The choice of the threshold value greatly impacts the performance of the impulse detector as it directly affects the number of false and missed detections. It has been observed that a single value of threshold is not optimum for different types of images and ideally it should be changed adaptively according to the contents of the filtering window [9].

Further, to overcome the problem of color artefacts in component-wise filtering scheme, color of filtered pixel may be restored separately using some suitable method. A filtering approach that employs separate color correction is given in [9], in which a VMF is followed by a VDF to obtain the magnitude and the angle information for restoration of the corrupted pixel. This scheme uses vector approach for both detection as well as filtering. However, it can be noted that the component-wise filtering approach provides a better estimate of the vector magnitude as in this case only the components of corrupted channels are modified, preventing the blurring caused by changes in noise free components. Now, the color artefacts generated in this scheme can be removed by using some color correction scheme. In this way, the ability of component-wise filtering approach to produce lower mean square error can be utilized.

In this paper, we present an impulse detection method where threshold is adaptively changed on the basis of local pixel statistics within the filtering window. This is followed by a filtering method which takes into consideration the color and brightness information to restore noisy pixels. The proposed method named as adaptive threshold and color correction (ATCC) filter, yields much better peak signal to noise ratio (PSNR), mean absolute error (MAE) and normalized color difference (NCD) than other methods as it combines the best features of both component-wise processing and vector processing approaches.

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2. Impulse detection

The impulse detection is based on the assumption that a noisy pixel takes a value which is substantially different than the neighbouring pixels in the filtering window, whereas noise-free regions in the image have locally smoothly varying values separated by edges. Let $\mathbf{x_{i,j}} = (x_{i,j}^{(1)},\ x_{i,j}^{(2)},\ x_{i,j}^{(3)})$ be a multi-channel pixel in the RGB space at location (i,j) of image I, which is corrupted by random valued impulse noise. If the noise ratio is p, then the observed pixel is given by:

$$\mathbf{x_{i,j}} = \begin{cases} \mathbf{o_{i,j}} \text{ with probability } (1-p) \\ \mathbf{n_{i,j}} \text{ with probability } p \end{cases}$$

where $\mathbf{o}_{i,j}$ and $\mathbf{n}_{i,j}$ represent the original and noisy pixels, respectively. Let us also define $w_{n\times n}^{(k)}$ as $(n \times n)$ filtering window for channel k with centre pixel $x_{i,j}^{(k)}$. Impulse detection is performed for each channel separately. First of all, the median, $med\ (w_{5\times 5}^{(k)})$, is subtracted from each pixel in the window $w_{5\times 5}^{(k)}$ to obtain the differences as:

$$w_{diff}^{(k)} = w_{5\times 5}^{(k)} - med(w_{5\times 5}^{(k)}); \quad k = 1, 2, 3 \tag{1}$$

Now for each channel k, the differences in the window $w_{diff}^{(k)}$ are arranged in ascending order as $\{d_{(1)}^{(k)}, d_{(2)}^{(k)}, \ldots, d_{(25)}^{(k)}\}$. Then a parameter $r_{(k)}$, defining the roughness of the filtering window is computed as:

$$r_{(k)} = \sum_{i=2}^{5} \frac{d_{(i)}^{(k)}}{4} \tag{2}$$

It is well known that the optimal threshold for impulse detection in an image is different for different locations depending upon the local contents and noise mixed in it. For example, if the filtering window is moving across a smooth region of an image then a small threshold is required to detect an impulse whereas if the region under consideration is rough a high threshold will be required. For this reason, an adaptive threshold, which depends on statistical characteristics of pixels within the window $w_{5\times 5}^{(k)}$ becomes an ideal choice. The proposed adaptive threshold for impulse detection, for each channel, is empirically obtained for natural images as:

$$T_{(k)} = 15 + 2.6 r_{(k)} \times \exp(-0.003 r_{(k)}^2) \tag{3}$$

The above expression of the adaptive threshold has been obtained by taking into consideration the variation of the difference between median and central pixel value in the filtering window with the parameter r_k for several natural images. The experiments revealed that except for higher values of r_k, the difference between median and central pixel value increases with increase in r_k and, therefore, the threshold should also be accordingly increased. The higher values of r_k are generated by the regions that contain smoothly varying edges. In these regions of image, the difference between median and central pixel value is small requiring smaller threshold for impulse detection. The threshold given by (3) produces the required variation for T_k effectively. The output of the detector is represented in terms of a flag image $\{\mathbf{f_{i,j}}\}$ where

$$f_{i,j}^{(k)} = \begin{cases} 1\ ;\ \text{if } x_{i,j}^{(k)} - med(w_{3\times 3}^{(k)}) \geq T_{(k)} \\ 0\ ;\ \text{otherwise} \end{cases} \quad \text{for } k = 1, 2, 3 \tag{4}$$

Here $f_{i,j}^{(k)} = 1$ implies that $x_{i,j}^{(k)}$ is noisy.

It can be noted that the impulse detector of [9], besides being computationally expensive, cannot effectively detect small errors present only in one or two channels as it is based on the difference in cumulative angles. Whereas, the detector described by (3) and (4) can effectively capture the noise level as well as the image characteristics in the filtering window and detects the presence of noise in each channel separately. The component-wise impulse detection is necessary if only noisy components are to be restored by the restoration filter.

2.1. Image restoration

In the first phase of filtering to restore the brightness, a directional weighted scheme, as used in [7], is considered. The weight of a pixel is decided on the basis of standard deviation in four pixel directions (vertical, horizontal and two diagonals). The brightness of the noisy pixel ($f_{i,j}^{(k)} = 1$) is restored as:

$y_{l,m}^{(k)} = med\left\{ w_{l,m} \lozenge\, x_{l,m}^{(k)} \right\}$; for all l and m such that $x_{l,m} \in w_{3\times 3}^{(k)}$ where operator $\lozenge$ denotes repetition operation and weights $\{w_{l,m}\}$ are defined as:

$$w_{l,m} = \begin{cases} 2;\ \text{if } x_{l,m}^{(k)} \in S \\ 1;\ \text{otherwise} \end{cases} \tag{5}$$

Here S denotes the set of pixels in the direction with minimum standard deviation. Now, the brightness restored multi-channel pixel is represented as $\mathbf{u_{i,j}} = (u_{i,j}^{(1)}, u_{i,j}^{(2)}, u_{i,j}^{(3)})$ where

$$u_{i,j}^{(k)} = \begin{cases} y_{i,j}^{(k)} \text{ if } f_{i,j}^{(k)} = 1 \\ x_{i,j}^{(k)};\ \text{otherwise} \end{cases} \quad \text{for } k = 1, 2, 3 \tag{6}$$

It is well known that VDF can provide the best possible color information about the filtered pixel. However, the magnitude of the filtered vector obtained from the VDF is not very reliable. Therefore, we use the color information provided by the VDF in the form of direction of the filtered pixel vector, along with the magnitude information obtained by (6) for better results. In the second phase of filtering, color of the filtered pixel at location (i,j) is restored by using the color information obtained from VDF. For this purpose, the output $\mathbf{v_{i,j}} = (v_{i,j}^{(1)}, v_{i,j}^{(2)}, v_{i,j}^{(3)})$ of the VDF is obtained from a 3×3 filtering window by considering noise free-pixels. A 5×5 is window is used if the number of noise-free pixels is less than four in 3×3 window. The final output after color restoration is given as $\mathbf{z_{i,j}} = (z_{i,j}^{(1)}, z_{i,j}^{(2)}, z_{i,j}^{(3)})$ where

$$z_{i,j}^{(k)} = \begin{cases} v_{i,j}^{(k)} \times ||\mathbf{u_{i,j}}||/||\mathbf{v_{i,j}}||;\ \text{if } f_{i,j}^{(k)} = 1 \\ u_{i,j}^{(k)};\ \text{otherwise} \end{cases} \tag{7}$$

3. Simulation results

To assess the performance of the proposed method, we compare it with several methods including VMF, VDF, DWM, HPD, hybrid vector filtering [9] and that of Jin et al. [8]. The test images used in simulations are 'Lena' and 'Boat in Lake' each of size 512×512. The test images are corrupted with 50% correlated random valued impulse noise with noise density varying from 5% to 30%.

The correlated noise is generated by color channel correlation technique as given in [4]. In this method, initially, each of the RGB channel is independently corrupted by the random valued impulse with probability p. Thereafter, a correlation factor 0.5 is used to simulate the error correlation between color components of the corrupted pixel.