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A salt & pepper noise filter based on local and global image information

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ABSTRACT

Existing salt & pepper noise filters only use local image information to detect noise pixels, and neglect global image information. This makes them inapplicable to images with noise-free pixel blocks composed of uncorrupted pixels of gray level extremes, either 0 or 255. In addition, existing filters are hard to simultaneously obtain low miss detection (MD) and low false alarm (FA) in noise detection. To alleviate these issues, we proposed an innovative noise filter based on local and global image information. The proposed filter developed an image block-based method to more accurately estimate noise density of an image, and presented a global image information-based noise detection rectification method. The noise density estimation result was used in subsequent noise detection and rectification stages. Furthermore, the proposed filter combined and slightly revised noise detection schemes of two existing switching filters to improve the accuracy of noise detection. Experimental results on a series of images showed that the proposed filter achieved significant improvement, especially on images with noise-free pixel blocks of gray level extremes.

1. Introduction

Salt & pepper noise, a classical type of image noise, usually emerges due to bit errors in the process of image acquisition and transmission [1–5]. It is one of the key factors causing image contamination and quality deterioration [6]. Salt & pepper noise pixels have gray level extremes, either 0 or 255, for an 8-bit image. Because a noise pixel usually differs from most of its local neighbors, it has the same large gradient value as an edge pixel. This coincidence between the noise pixel and the edge pixel causes great difficulty for image analysis, especially for edge detection [7]. How to effectively remove salt & pepper noise is still of great importance to image denoising.

During the past several decades, many different types of filters have been developed to remove salt & pepper noise. Median filter is one of the most popular nonlinear filters for removing salt & pepper noise in terms of its good denoising capability [1] and computational efficiency [8]. Unfortunately, when noise density is higher than 50%, some image details are blurred by median filter [9]. Denoising performance of median filter relies on the size of filtering window. Increment of window size will enhance its denoising capability. However, a large filtering window is prone to generate blurry image details due to its undiscriminating gray level replacement operation on each pixel. To alleviate the issue, many modified versions [10–13] of median filter were developed. For example, Adaptive median filter (AM) [13] automatically adjusts the size of filtering window according to local patch of each noise pixel.

Conventional filters unconditionally apply the gray level replacement operation to each image pixel, and do not consider whether the current pixel is a noise pixel. Noise-free pixels, which contribute much to image details, are also subject to the replacement operation. This causes degradation of image quality. To alleviate the issue, switching filters [14–23], a popular type of noise removal techniques, emerge accordingly. Switching filters first detect noise pixels in an image, and then only implement the gray level replacement operation on noise pixels. Modified decision based unsymmetric trimmed median (MDBUTM) filter [17] detects noise pixels via the characteristic of gray level extremes (0 and 255), and then adaptively chooses the mean or median variant of each noise pixel's 3×3 filtering window as its restored gray level according to the number of gray level extremes in the filtering window. Switching median filter with boundary discriminative noise detection (BDND)

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[18] uses a two-stage detection scheme with different filtering window sizes to identify noise pixels, and replaces each noise pixel with the median of remaining pixels excluding noise neighbors in its adaptive filtering window. The second stage (validation stage) of BDND's noise detection lacks statistical significance due to the small local window of 3×3. To remedy the issue, highly effective impulse noise detection (HEND) method [19] uses directional gray level differences to further affirm noise pixels in validation stage. HEND only involves noise detection. Directional weighted median (DWM) filter [20] uses the minimum sum of directional weighted gray level differences to detect noise pixels, and replaces each noise pixel with the weighted median of its filtering window. Differing from DWM, its modified version (MDWM) [21] considers more edge directions in noise detection, and takes the weighted median excluding gray level extremes on the optimum direction of filtering window as the restored gray level of current noise pixel. After deeply analyzing the limitations of DWM and MDWM in noise restoration, MDWF [22] presents a novel noise restoration scheme, which adaptively takes the weighted mean of each noise pixel's recursive or non-recursive filtering window as its restored gray level. Switching-based adaptive weighted mean (SAWM) filter [23] uses another form of directional gray level difference to detect noise pixels, and takes the weighted mean of adaptive filtering window to restore each noise pixel.

After exploring salt & pepper noise filters, we found two limitations of their noise detection schemes. One is that they only use local image information such as directional gray level differences of a local window to detect noise pixels, but neglect global image information. This makes them inapplicable to images with noise-free pixel blocks of gray level extremes, either 0 or 255. The other limitation is that they fail to simultaneously obtain low miss detection (MD) and low false alarm (FA) [19] in noise detection. To alleviate these issues, we present an innovative filter based on local and global image information. Experimental results on a series of images showed that the proposed filter outperformed the counterparts, especially for images with noise-free pixel blocks of gray level extremes.

The rest of this paper is organized as follows: Section 2 briefly introduces noise detection schemes of two existing switching filters related with the proposed filter, and analyzes their limitations. Section 3 describes theory and implementation of the proposed filter. Performance comparison between the proposed filter and other filters is arranged in Section 4. Conclusions appear in Section 5.

2. Noise detection of two existing switching filters

The proposed filter was mainly inspired to solve the deficiencies of existing salt & pepper noise filters in noise detection. During exploring switching filters, we found that SAWM and MDWF usually have better image denoising effect. However, both of them still have some limitations in noise detection. The proposed filter aims to combine their advantages and rectify their errors in noise detection. This section will review the noise detection schemes, SAWM_D and MDWF_D, of SAWM and MDWF, and analyze their limitations.

2.1. SAWM_D

SAWM_D [23] uses directional weighted gray level difference to detect noise pixels in an image. The detailed process of noise detection is as follows:

(1) For a given pixel $p_{i,\ j}$, acquire the $L_d \times L_d$ local window Ω centered at $p_{i,\ j}$.
(2) Sort all gray levels (elements) in Ω into ascending and form a vector F, find the r-th and z-r+1-th elements, F_r and F_{z-r+1}, where z= $L_d \times L_d$ and $1 \le r \le$ (z-1)/2. The parameter r is set to 1 in [23]. In this case, F_r and F_{z-r+1} respectively denote the minimum and maximum gray level in Ω. Note that, the minimum gray level may be not 0, and the maximum level may be not 255.
(3) Construct a gray level interval R for Ω, where R is defined as

$$R = (F_r \;\; F_{z-r+1}). \tag{1}$$

In Ω, those pixels with gray levels outside of R are regarded as noise candidates, and we use Ω_1 to denote the set after excluding noise candidates.
(4) Calculate absolute weighted mean value of gray level differences between $p_{i,\ j}$ and the noise-free neighbors on certain direction k of Ω_1, where k $(1 \le k \le 4)$ is direction index. Because incorporation of more directions can only slightly improve noise detection accuracy at the expense of the increasing computational complexity, only 4 common edge directions (0, π/4, π/2, and 3π/2) are considered.

$$\overline{d}_{i,j}^{(k)} = \begin{cases} \dfrac{\left|\sum_{p_{s,t} \in \Omega_1^{(k)}} \omega_{s,t} d_{s,t}\right|}{\sum_{p_{s,t} \in \Omega_1^{(k)}} \omega_{s,t}}, & if\ \Omega_1^{(k)} \ne \Phi \\ F_{z-r+1} - F_r, & otherwise \end{cases} \tag{2}$$

$$\omega_{s,t} = \frac{1}{1 + |d_{s,t}|^2}, \tag{3}$$

$$d_{s,t} = f_{s,t} - f_{i,j}, \tag{4}$$

where Φ denotes the null set, $\Omega_1^{(k)}$ is the subset of Ω_1 on k-th direction, $f_{s,\ t}$ and $f_{i,\ j}$ are the gray levels of $p_{s,\ t}$ and $p_{i,\ j}$, respectively.
(5) Find the minimum of four absolute weighted mean values, and denote it as

$$d_{i,j} = arg\ \min_k \{\overline{d}_{i,j}^{(k)},\ \ 1 \le k \le 4\}. \tag{5}$$

(6) Identify salt & pepper noise and construct a binary label matrix as

$$B_{i,j} = \begin{cases} 1, & if\ \ d_{i,j} > T_1 \\ 0, & otherwise \end{cases} \tag{6}$$

where T_1 is a parameter, 1 and 0 denote noise pixel and noise-free pixel, respectively.

2.2. MDWF_D

MDWF_D detects noise pixels by using another form of directional weighted gray level difference and gray level extreme judgment. The detailed process of noise detection is as follows:

(1) For a given $m \times m$ local window Ω centered at pixel $p_{i,\ j}$ of gray level $f_{i,\ j}$, calculate sum of absolute weighted gray level differences between $p_{i,\ j}$ and its neighbors on certain direction k:

$$d_{i,j}^{(k)} = \sum_{p_{s,t} \in \Omega^{(k)}} w_{s,t} |f_{s,t} - f_{i,j}|, \quad (s,t) \ne (i,j), \tag{7}$$

$$w_{s,t} = \begin{cases} 2, & (s,t) \in \Omega_3 \\ 1, & otherwise \end{cases} \tag{8}$$

$$\Omega_3 = \{(s,t) : -1 \le s-i \le 1, -1 \le t-j \le 1\}, \tag{9}$$