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A weighted mean filter with spatial-bias elimination for impulse noise removal

Cengiz Kandemir, Cem Kalyoncu, Önsen Toygar *

Computer Engineering Department, Eastern Mediterranean University, Gazimağusa, Northern Cyprus, Mersin 10, Turkey

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A B S T R A C T

In this paper, we propose Unbiased Weighted Mean Filter (UWMF) for removing high-density impulse noise. Asymmetric distribution of corrupted pixels in the filtering window creates a spatial-bias towards the center of uncorrupted pixels. UWMF eliminates this bias by recalibrating the contribution factor (weight) of each uncorrupted pixel in such a way that the center shifts back to the center of the filtering window. The restoration process involves three sequential operations while convolving a filtering window over a contaminated image. Noise is detected, weights are recalibrated and the new intensity value is replaced by weighted mean using the recalibrated weights. Compared to the state-of-the-art impulse noise removal methods, UWMF provides superior performance, without requiring a fine-tuning for its parameters, in terms of both objective measurements and subjective assessments.

1. Introduction

Contamination of digital images by impulse noise often occurs during image acquisition or transmission. Two types of impulse noise are random-valued and fixed-valued (salt-and-pepper). The former type corrupts a pixel with an intensity value within a range in an additive manner [1]. The latter type — salt-and-pepper noise manifests itself with the highest or the lowest possible intensity value on a given pixel. This study focuses on fixed-valued impulse noise. Human visual system is sensitive to the presence of impulse noise [2]. Furthermore, such contamination may decrease the suitability of digital images for computer vision applications such as motion detection [3–5], surveillance systems [6], image and video encoding/compression [7,8] due to undesirable high-frequency components [9]. Therefore, it is vital to restore these images for visual applications and further processing. Various filters have been proposed to remove impulse noise over the years. Amongst them, Standard Median Filter is a well-known method that is widely used due to its fine detail preservation capabilities. However, its performance declines at higher noise densities [10]. This situation led researchers to concentrate on improving median-based filters [2,9–18]. Similarly, many mean-based filters have been shown to be successful for removing impulse noise [19–22]. Moreover, switching-based filters are introduced with the intuition of applying filter to those pixels that are corrupted. In these methods, corrupt pixels are detected before proceeding into filtering stage [2,9,11,12,20,23,24].

In [21], authors propose a method named Adaptive Weighted Mean Filter (AWMF). AWMF operates in a similar way to Adaptive Median Filter (AMF) [16]. It adaptively increases the filtering window size until two successive windows have equal minimum and maximum value. Then, each pixel is assigned to a binary weight (0 or 1) depending on minimum and maximum intensity value in the filtering window and the central pixel is replaced with weighted mean.

Interpolation-Based Impulse Noise Removal (IBINR) is proposed in [19]. IBINR assigns weights to uncorrupted pixels in the filtering window based on their Euclidean distance to center, then it replaces central pixel with a weighted mean. This method provides robust restoration performance while maintaining computational efficiency.

Various improvements over Boundary Discriminative Noise Detection (BDND) filtering stage are proposed in [9]. In their efforts to improve the filtering stage of BDND, the authors focus on expansion condition of the filtering window and incorporation of spatial distance.

Cloud Model Filter (CMF), proposed by Zhou [20], employs Cloud Model [25] for detection stage. It exploits randomness and fuzziness involved in impulse noise. A weighted fuzzy mean filter is used in filtering stage. CMF successfully detects impulse noise with total misclassification rate less than 0.01% at higher noise densities while its detection rate diminishes slightly at lower noise densities.

* Corresponding author.
E-mail address: onsen.toygar@emu.edu.tr (Ö. Toygar).

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In [10], authors proposed a variant of median filter, namely, Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF). MDBUTMF ignores corrupt pixels while ordering intensity values in the filtering window. The central pixel is replaced by the median value of the trimmed pixel set.

Another switching-based adaptive median filter is called Noise Adaptive Fuzzy Switching Median Filter (NAFSMF) [12]. NAFSMF expands filtering window while searching for uncorrupted pixels. Upon finding enough uncorrupted pixels, median in current window is selected for restoration. However, expansion stops on a predetermined window size if no uncorrupted pixels are found. In such a case, a new 3×3 window is imposed and median of the first four pixels in the upper-left region is selected for restoration.

Ng and Ma [11] incorporated Noise Adaptive Soft-Switching Median Filter (NASMF) [2] with Boundary Discriminative Noise Detection (BDND). BDND forms three intensity clusters as lower intensity impulse noise, uncorrupted pixels and higher intensity impulse noise by calculating lower and higher intensity boundary values using intensity differences between pixels. In filtering stage, a modified version of NASMF is used. BDND shows robust detection performance even at high noise densities with total misclassification rate less than 1%.

Noise Adaptive Soft-Switching Median Filter (NASMF) [2] differentiates pixels into four classes as uncorrupted pixels, isolated impulse noise, non-isolated impulse noise and edge pixels, using local and global pixel statistics. Different filtering methods are applied for different classes. Isolated and non-isolated impulse noise are restored with SMF; edge pixels are restored with a fuzzy weighted median filter. NASMF performs well with lower noise densities. However, at higher noise densities, it fails to restore fine details due to incorrect classification of pixels.

In many filters, a selection of uncorrupted pixels is applied before or during filtering stage. The selection process does not consider the positional distribution of corrupted pixels in the filtering window. When these pixels are distributed asymmetrically, such approaches will lead to a spatial-bias towards the center of uncorrupted pixels. In this paper, we propose Unbiased Weighted Mean Filter (UWMF) to eliminate this bias by recalibrating the contribution factor (weight) of uncorrupted pixels. Experiments show that the proposed method has superior results in terms of both objective measurements and subjective assessments. The rest of the paper is organized as follows. In Section 2, the rationale behind the proposed method and further details are given. In Section 3, simulation results are rendered. Finally, the paper is concluded in Section 4.

2. Unbiased weighted mean filter

Unbiased Weighted Mean Filter performs three operations in a sequential manner while convolving a filtering window over a contaminated image. These are noise detection, spatial-bias elimination and noise removal by calculation and assignment of new intensity values to the corrupted pixels. However, in order for weight recalibration to take place, a priori distribution of weights is required. In subsequent subsections, these three procedures will be explained.

2.1. Noise detection

Unbiased Weighted Mean Filter employs a simple noise detection procedure similar to many methods in the literature [10,19,26–28]. Impulsive interferences to image signal produce extreme intensities. Therefore, impulse noise can be defined as follows

$$c_{x,y} = \begin{cases} i_{min}, & q \\ i_{max}, & q \\ o_{x,y}, & 1-(2q) \end{cases} \tag{1}$$

where o is the original image, c is the contaminated image and (x, y) represents a pixel coordinate. q represents the probability of corruption for extrema (i_{min} and i_{max}). Using (1), a pixel is identified as corrupted if it has the lowest (i_{min}) or the highest (i_{max}) intensity value. The lowest and the highest intensity values for an 8-bit grayscale image are 0 and 255, respectively. In a more rigorous sense, the set of corrupted pixels (I_η) in the filtering window is defined as follows

$$\begin{aligned} I_0 &= \{(x, y) \mid i_{x,y} = 0 \wedge i_{x,y} \in I\} \\ I_{255} &= \{(x, y) \mid i_{x,y} = 255 \wedge i_{x,y} \in I\} \\ I_\eta &= I_0 \cup I_{255} \end{aligned} \tag{2}$$

I represents all pixels in the filtering window where $-\frac{wsize-1}{2} \le x, y \le \frac{wsize-1}{2}$ and $wsize$ is the size of filtering window. $i_{x,y}$ is the intensity value of the pixel at coordinates (x, y) in the filtering window. I_0 represents the set of pixels with intensity value 0 (black) and I_{255} represents the set of pixels with intensity value 255 (white).

2.2. Elimination of the spatial-bias

Spatial-bias elimination takes place after noise detection. This operation requires a weight distribution. Spatial-bias is eliminated by analyzing the distribution of corrupted pixels in the filtering window and recalibrating the weights accordingly.

2.2.1. Weight distribution

The proposed solution to spatial-bias elimination requires presence of weights. The first step of spatial-bias elimination is to distribute weights based on their distance to the central pixel which are calculated as

$$w_{x,y} = [\Phi((x, y), (0, 0))]^{-k} \tag{3}$$

where $\Phi(\cdot)$ is a function calculating the distance between a location (x, y) and the central location of the filtering window. k is a parameter of the system which controls the mitigation of weights based on the distance to the central pixel. The pixels that are further away relative to the center of the filtering window are less spatially-correlated than those that are close. Thus, it is important to diminish contribution of distant pixels. In this study, we have used Minkowski Distance defined as

$$D_{Minkowski}(Q, R) = \left(\sum_{l=1}^{L} |Q_l - R_l|^p \right)^{1/p} \tag{4}$$

where p is a parameter of distance metric and L is the number of dimensions. When p is 1 or 2, it corresponds to Manhattan or Euclidean Distances, respectively. These two values of p are found to be yielding the highest restoration performance (explained in Section 3.3). According to the empirical results, the value of k is estimated to be between 4 and 6; and p to be 1 (Manhattan Distance). However, the effect of changing values of p is not significant in terms of restoration quality. Details of parameter effects are presented under Section 3.3. The distributed weights are used for recalibration, however, their values need not to be changed during convolution and all parameters (p, k, and $wsize$) are known a priori. Therefore, it is suggested to calculate weights and store them in a matrix, in order to be used later for recalibration during convolution.

2.2.2. Spatial-bias

It is essential to understand the nature of the spatial-bias and why it needs to be eliminated. While estimating the original value