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A new adaptive switching median filter for impulse noise reduction with pre-detection based on evidential reasoning

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ABSTRACT

Image denoising is a fundamental problem in image processing. The switching filtering is a popular approach to reduce the impulse noise. It faces two challenges including the impulse noise detection and filter design. The traditional detection methods based on single criterion or multiple criteria encounter uncertainty problems and produce many miss-detections and false alarms, especially when the image is severely corrupted. In this paper, the uncertainties encountered in the impulse noise detection are addressed using the theory of belief functions, and a multi-criteria detection strategy for the impulse noise based on evidential reasoning is proposed. Based on the pre-detection, an adaptive median filter is designed, which adaptively determines the size of the filtering window according to the estimated global noise density and the degree of local corruption. Experimental results and related analyses show that our proposed image denoising method for the impulse noise has superior performance compared with several state-of-the-art denoising methods.

1. Introduction

Digital images can be corrupted by various types of noise during the image acquisition and transmission. The impulse noise is one of the most common types, which is encountered in cases with quick transients, e.g., faulty switching during imaging [1]. The intensity of a pixel corrupted by the impulse noise tends to be much higher or lower than those of its uncorrupted neighbors. The impulse noise dramatically influences the image quality and makes images unsuitable for subsequent human understanding or image processing such as the edge detection [2], segmentation [3], object recognition [4], image analysis [5] and image understanding [6].

Till now, the impulse noise reduction problem has not been well solved and has attracted extensive research interests. The median filtering is the most popular approaches for the impulse noise reduction. The standard median (SM) filter [7] replaces the target pixel's intensity by the median of intensities of its neighbors. Various modifications of the SM filter have been proposed, such as the weighted median (WM) filter [8] and the center weighted median (CWM) filter [9]. However, all these filters apply the median operations to each pixel ignoring whether the target pixel is corrupted or not. This might destroy the details contributed from uncorrupted pixels and lead to image quality degradation. To deal with this problem, switching median filters [10] were proposed, which introduce the noise detection prior to the filtering. Since only the corrupted pixels will be filtered and the uncorrupted pixels remain intact, more details can be preserved and better filtering performance can be achieved if the pre-detection result is accurate enough.

In recent years, sparse representation (SR) [11] is widely used in image denoising [12–14], especially for Gaussian noise. For the impulse noise, the noise detector is incorporated into SR model and the weighted dictionary learning method was proposed for impulse noise denoising [15–17]. Both median filtering and SR based method face the challenge of noise detector designing.

There have emerged two major criteria for the impulse noise detection including the extreme property and discontinuity property. Some detectors only use a single criterion, which may involve some uncertainty problems. For example, the boundary discriminative noise detection (BDND) [18] and the efficient improvements on the BDND (IBDND) [19] use the criterion of extreme property. Both algorithms label a pixel as the noise if it is assigned to the low-intensity range or high-intensity range according to the histogram distribution in a local window centered at that given pixel. However, these detectors easily lead to false alarms since not all the pixels with low-intensity or high-intensity are noise. There are

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other detectors that only use the criterion of discontinuity property. Such detectors can be found in the adaptive impulse detection using center-weighted median (ACWM) filter [20], directional weighted median (DWM) filter [21], contrast enhancement-based (CEF) filter [22], adaptive switching median (ASWM) filter [23], weighted couple sparse representation (WCSR) model [24] and the denoising framework combining the detection mechanism based on the robust outlyingness ratio with the NL-means (ROR-NLM) [25]. They label a pixel as the noise if its similarity with its neighbors is lower than a preset threshold. However, when the noise density is high, the impulse noise pixels might not show the discontinuity property since there are too many noise pixels in their neighbors. Since pixels with extreme or discontinuity property may not always be the noise, the detectors based on a single criterion will involve uncertainty problems and tend to yield incorrect detection results. Both criteria have their own rationalities; however, they are one-sided. It should be better to jointly use them when detecting the impulse noise. Therefore, some approaches using the above two criteria jointly have been proposed, e.g., the detector in noise adaptive soft-switching median (NASM) filter [26] and the detector based on the cloud model (CM) [27]. These two-step detection methods first recognize the suspected noise pixels using the extreme criterion, and then distinguish the noise pixels from the suspected noise pixels using the discontinuity criterion. However, they can easily produce miss-detections when some noise pixels are not detected as the suspected noise in the first step. Therefore, the two-step type joint use is not preferred.

To deal with the uncertainties encountered in the impulse noise detection and avoid the drawbacks of the two-step-type joint use of detection criteria, in this paper, a new detection approach for the impulse noise is proposed, which uses the two criteria simultaneously based on the theory of belief functions [28]. In our detection approach, the extreme property is described using the interval data distance between the target pixel's intensity and the intensity range of the whole noisy image (expressed as an interval number). The discontinuity property is described using the rank-ordered absolute differences (ROAD) statistic [29]. The uncertainty problem encountered in the impulse noise detection, e.g., pixels with extreme or discontinuity property may not always be the noise, are modeled by belief functions and are further handled through the evidence combination.

The impulse noise detector implementation is the main work of this paper. Based on the detection result, an adaptive median filter is designed, which adaptively determines the size of filtering window according to the estimated global noise density and local corrupted degree. Experimental results show that our proposed adaptive switching median filter with pre-detection based on evidential reasoning (ASMF-DBER) has superior performance compared with several state-of-the-air switch median filters and the SR based method.

2. Basis of impulse noise and uncertainty problems encountered in impulse noise detection

2.1. Impulse noise model

When an image is corrupted by the impulse noise, some pixels are changed and their intensities are extremely high or extremely low. We use the same impulse noise model as used in BDND [18]. Assume that the noise pixels take values in two fixed sets $S_1 = \{0, 1, \ldots, \alpha\}$ and $S_2 = \{255-\alpha, 255-(\alpha-1), \ldots, 255\}$ for an 8-bit monochrome image. Let $s_{i,j}$ and $x_{i,j}$ be the pixels' intensities at location (*i, j*) in the original and noisy images, respectively. Let $n_{i,j}$ be the noise which is independent of $s_{i,j}$ and corresponds to a random value uniformly distributed in the set S_1 and S_2. Let p denote the probability that a pixel is corrupted. The probability mass function (pmf) [30] of $x_{i,j}$ is given by

$$P(x_{i,j}) = \begin{cases} p, & \text{for } x_{i,j} = n_{i,j}, \\ 1-p, & \text{for } x_{i,j} = s_{i,j}. \end{cases} \quad (1)$$

Specially, if $\alpha = 0$, the intensities of noise pixels can only take the two extreme values 0 or 255. This type of impulse noise is also called the salt-and-pepper noise. Since $n_{i,j}$ is independent of $s_{i,j}$, it is possible that $n_{i,j} = s_{i,j}$. This kind of pixel should be regarded as uncorrupted.

2.2. Uncertainties encountered in impulse noise detection

The impulse noise has two properties:

(a) *Extreme property*: The intensity of an impulse noise pixel is usually an extreme value (0 or 255) or close to an extreme value.
(b) *Discontinuity property*: The intensity of an impulse noise pixel tends to be much higher or lower than those of its neighbors.

These two properties are often used as detection criteria for the impulse noise. Some detectors only use one of the criteria:

(a) Detectors based on the criterion of extreme property: These detectors label a pixel as the noise, if it is assigned to the low-intensity range or high-intensity range according to the histogram distribution in a local window centered at that pixel, e.g., BDND [18] and IBDND [19] detectors.
(b) Detectors based on the criterion of discontinuity property: These detectors label a pixel as the noise, if its dissimilarity with its neighbors is larger than a preset threshold, such as ACWM [20], DWM [21], CEF [22], ASWM [23], ROR-NLM [25] and WCSR [24].

However, such single criterion based detectors may involve the following uncertainty problems:

(a) Uncertainty in extreme criterion: Some signal pixels may also be detected as the noise, since their intensities are very close to extreme values, e.g., some edge pixels and texture pixels. Moreover, in some bright or dark area, the intensity range of signal pixels may overlap with that of the impulse noise pixels. Therefore, when using the extreme criterion alone, it is uncertain to judge those signal pixels with extreme property to be the impulse noise or not.
(b) Uncertainty in discontinuity criterion: The discontinuity property of the impulse noise pixels becomes weaker with the increase of noise density since there are many noise pixels in their neighbors. At the same time, some signal pixels may show discontinuity. Therefore, with only the discontinuity criterion, it is uncertain to judge a pixel to be the impulse noise or not.

Due to these uncertainties, the single criterion based detectors are to some extent one-sided and tend to yield incorrect detection results. Hence, it should be better to jointly use the two criteria to implement a more comprehensive detection.

Some two-step detection methods, like NASM [26] and CM [27], jointly use these two criteria in two consecutive steps. They first recognize suspected noise pixels according to the extreme criterion, and then distinguish noise pixels from suspected noise pixels according to the discontinuity criterion, as illustrated in Fig. 1. In the first step, only using the extreme criterion, some noise pixels may not be detected as the suspected noise and therefore are miss-detected straightly. These miss-detected pixels will not undergo the filtering so that these two-step methods can easily lead to poor noise-reduction capabilities. Therefore, when detecting the