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A two-stage shearlet-based approach for the removal of random-valued impulse noise in images ☆

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ABSTRACT

In this paper, we introduce a novel two-stage denoising method for the removal of random-valued impulse noise (RVIN) in images. The first stage of our algorithm applies an impulse-noise detection routine that is a refinement of the HEIND algorithm and is very accurate in identifying the location of the noisy pixels. The second stage is an image inpainting routine that is designed to restore the missing information at those pixels that have been identified during the first stage. One of the novelties of our approach is that our inpainting routine takes advantage of the shearlet representation to efficiently recover the geometry of the original image. This method is particularly effective to eliminate jagged edges and other visual artifacts that frequently affect many RVIN denoising algorithms, especially at higher noise levels. We present extensive numerical demonstrations to show that our approach is very effective to remove random-valued impulse noise without any significant loss of fine-scale detail. Our algorithm compares very favourably against state-of-the-art methods in terms of both visual quality and quantitative measurements.

1. Introduction

Random-valued impulse noise (RVIN) is a common cause of image degradation, frequently found in images acquired from digital cameras and is usually due to malfunctioning camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. RVIN is characterized by the alteration of specific pixels in an image with the result that their intensity values become incompatible with the neighboring pixels [1]. The presence of impulse noise may severely corrupt the information embedded in the original data and it is critical to correct the image degradation before subsequent image processing tasks such as edge detection, feature extraction or classification.

Non-linear filters such as median (MED) filters are popular techniques for removing RVIN because of their simplicity and low computational cost [1,2]. However, conventional median filters apply the median operation unconditionally, that is, without discriminating between corrupted and uncorrupted pixels. As a result they modify both noisy and noise-free pixels alike causing loss of image detail that may be especially significant at higher noise levels.

To overcome these limitations, an effective strategy consists in applying first an impulse-noise detection routine so that only the noisy pixels would undergo a filtering process. Several *two-stage* denoising algorithms have been proposed based on this processing strategy, most notably the directional weighted median filer (DWM) [3], the switching median filter with boundary discriminative noise detection (SM-BDND) [4], the direction-based adaptive weighted switching median filter (DAWSM) [1] and the homogeneous amount based (HAB) filter [5]. The efficiency of these two-stage denoising schemes clearly depends on the combined efficiency of impulse detection and filtering routines used. The DWM, in particular, uses a direction-based approach to detect noisy pixels that computes the difference between a pixel and its neighbors within a window of size 5; the detected noisy pixels are then replaced by the output of a directional weighted median filter [1]. The SM-BDND algorithm applies the boundary discriminative noise detection method to detect noisy pixel positions; detected noisy pixels are then replaced by the median value of the pixels in the filtering window. The DAWSM algorithm uses a sophisticated impulse-noise detection method, called Highly Effective Impulse Noise Detection algorithm (HEIND), originally proposed by Duan and Zhang [6]. HEIND uses both boundary and directional information to detect noisy pixels; after the detection

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stage, the noisy pixels are replaced by the weighted median value of uncorrupted pixels in a directional filtering window. The Fuzzy Weighted Non-Local Means method (FWNLM) proposed by Wu and Tang [7] that uses a fuzzy weighting function with the non-local means algorithm to selectively pick pixels when calculating the pixel similarity. We also recall the multistage denoising method by two of the authors in [8], which uses a simple directional filter similar to the method in [2] to detect noisy pixels, followed by a total-variation inpainting routine.[2]

Although multistage RVIN denoising schemes perform consistently better than conventional median filters, they frequently produce jagged edges and introduce visual artifacts, such as block effects, in the processed images especially at higher noise levels. This limitation is due to the fact that, even though these algorithms can efficiently estimate the location of noisy pixels and enforce compatibility among neighboring pixels, they are usually not very efficient in recovering the *geometry of the corrupted data*. This is particularly evident at higher noise levels, where the problem of recovering the information at the locations of corrupted pixels is more challenging. This observation is indeed the motivation for some recent work in [9], where the denoising algorithm includes a routine designed to recover the edge information, and [5], where the task to restore the corrupted information is handled by a total-variation inpainting method.

In this paper, we propose a novel two-stage algorithm for restoring data affected by RVIN which includes, as a first stage, a very efficient impulse-noise detector that we obtain as a refinement of the HEIND algorithm and, as a second stage, an innovative shearlet-based image inpainting routine to restore the corrupted pixels. The main advantages of our approach are due to (1) the improved method for impulse-noise detection and (2) the application of the image inpainting routine, taking advantage of the properties of shearlets to efficiently recover the geometry of the original image. The shearlet representation, introduced by one of the authors and his collaborators, is an advanced multiscale method providing optimal approximation properties for images with edges. It was recently proven that shearlets have a superior ability to recover occluded edges and their application to image inpainting can significantly outperform other conventional inpainting algorithms [10].

As a part of this work, we numerically analyze the performance of our denoising algorithm and present extensive numerical demonstrations on images degraded by two classical types of random-valued impulse noise with a wide range of noise levels varied from 10% to 80%. We compare our algorithm against a range of conventional and state-of-the-art denoising schemes, including the median filer (MED), the modified noise adaptive soft switching median filter (MNASM) with HEIND detector [6] (H-MNASM), the SM-BDND method [4], the FWNLM method [7] and the DAWSM method [1]. We have also included the comparison with a version of our algorithm containing another more traditional inpainting method, based on total variation. The experimental results reported in this paper show that our algorithm is extremely competitive for RVIN denoising and outperforms current state-of-the-art algorithms in terms of visual quality and objective measures. In particular, our approach virtually eliminates jagged edges and other visual artifacts which are frequent in other RVIN denoising algorithms, especially at higher noise levels.

The rest of the paper is organized as follows. In Section 2, we present our new two-stage denoising algorithm, combining an improved method for the detection of RVIN (Section 2.2) and a powerful image inpainting method (Section 2.3). In Section 3, we provide extensive numerical experiments to validate our algorithm even under very challenging noise conditions and compare our results against several other state-of-the-art denoising methods. We conclude with some remarks in Section 4.

[2] This algorithm is specifically designed to handle salt and pepper noise, and both its noise-detection and inpainting routines are much less sophisticated than those that will be considered in this paper.

2. Proposed random-valued impulse noise detection method

As indicated above and illustrated in Fig. 1, in this paper we adopt a two-stage denoising strategy. The first stage of our algorithm is devoted to detect the location of the pixels affected by impulse noise. Once the noisy pixels are detected, they are handled as missing pixels that need to be restored. Hence, the second stage of our algorithm is an image inpainting routine designed to recover the information at the noisy pixel locations.

Before presenting the detailed description of the two stages of our algorithm, we briefly review the noise models that are considered in this paper.

2.1. Impulse-noise models

Four impulse-noise models are usually described in the literature [1,4].

1. Noise Model 1. The simplest impulse-noise model is the *salt-and-pepper* noise where pixels are randomly corrupted by two fixed extreme values, usually 0 and 255 (for 8-bit grayscale images), with the same probability. That is, for each pixel location (i,j) in the image, with intensity value $s_{i,j}$, the corresponding pixel in the noisy image is $x_{i,j}$ where the probability density function of $x_{i,j}$ is
$$f(x) = \begin{cases} p/2 & \text{for } x = 0 \\ 1-p & \text{for } x = s_{i,j} \\ p/2 & \text{for } x = 255 \end{cases}$$
and p is the noise density $(0 < p < 1)$.
2. Noise Model 2. It is similar to Model 1, with the difference that the probabilities of "salt" and "pepper" are unequal. That is, the probability density function of $x_{i,j}$ is
$$f(x) = \begin{cases} p_1 & \text{for } x = 0 \\ 1-p & \text{for } x = s_{i,j} \\ p_2 & \text{for } x = 255 \end{cases}$$
where $p = p_1 + p_2$ with $p_1 \neq p_2$ (and $0 < p < 1$).
3. Noise Model 3. Instead of taking two *fixed values*, impulse-noise is modeled by two *fixed ranges* of same length m, that appear at both ends of the integer range. This definition provides a more realistic modeling of noise found in practical applications, such as medical imaging [4,11]. In this setting, the probability density function of $x_{i,j}$ is
$$f(x) = \begin{cases} p/2 & \text{for } 0 \leqslant x < m \\ 1-p & \text{for } x = s_{i,j} \\ p/2 & \text{for } (255-m) < x \leqslant 255 \end{cases}$$
where p is the noise density $(0 < p < 1)$.
4. Noise Model 4. It is similar to Model 3, with the difference that the probabilities of low intensity impulse noise and high intensity impulse noise are unequal. Hence the probability density function of $x_{i,j}$ is
$$f(x) = \begin{cases} p_1 & \text{for } 0 \leqslant x < m \\ 1-p & \text{for } x = s_{i,j} \\ p_2 & \text{for } (255-m) < x \leqslant 255 \end{cases}$$
where $p = p_1 + p_2$ with $p_1 \neq p_2$ (and $0 < p < 1$).