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An automatic filtering convergence method for iterative impulse noise filters based on PSNR checking and filtered pixels detection

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ABSTRACT

Whether input images are corrupted by impulse noise and what the noise density level is are unknown a priori, and thus published iterative impulse noise filters cannot adaptively reduce noise, resulting in a smoothing image or unclear de-noising. For this reason, this paper proposes an automatic filtering convergence method using PSNR checking and filtered pixel detection for iterative impulse noise filters. (1) First, the similarity between the input image and the 1st filtered image is determined by calculating MSE. If MSE is equal to 0, then the input image is unfiltered and becomes the output. (2) Otherwise, one applies PSNR checking and filtered pixel detection to estimate the difference between the *t*th filtered image and the *t*−1th filtered image. (3) Finally, an adaptive and reasonable threshold is defined to make the iterative impulse noise filters stop automatically for most image details preservation in finite steps. Experimental results show that iterative impulse noise filters with the proposed automatic filtering convergence method can remove much of the impulse noise and effectively maintain image details. In addition, iterative impulse noise filters operate more efficiently.

1. Introduction

Image processing techniques require a noise-free environment, but digital images are often corrupted by impulse noise due to channel transmission errors, noisy sensor, or faulty memory locations in hardware (Gonzalez & Woods, 2002). Impulse noise can be classified as salt-and-pepper noise and random-valued noise, and it seriously affects the performance of image processing techniques, e.g., pattern recognition, image segmentation, image compression, etc. Therefore, impulse noise reduction is a preprocessing module for preserving fine details and edge elements.

Filtering impulse noise to improve the quality of an image has been the focus of attention over many years. A good image filtering technique for image restoration is able to suppress the noise while preserving the natural information of the original images (Gonzalez & Woods, 2002). A huge number of non-linear filtering techniques, which are in general better performers than linear filtering techniques, have been proposed for achieving this goal. However, whether the input images are corrupted by impulse noise and what the noise density level is are unknown a priori. To improve the performance of these published non-linear filtering techniques, the details of an image should be first estimated for reducing noise and for adaptively preserving the original details.

It is a fact that the original details of an image will affect the performance of non-linear filtering techniques. Corrupted pixels belonging to low-frequency signals of an image are easily detected and removed, because the difference is large between the corrupted pixel and the noise-free pixel. Therefore, non-linear filtering techniques can present good performance in images that include many low-frequency signals. In order to suppress the noise as much as possible in an image corrupted with a high-density level of noise, iterative non-linear filtering techniques are proposed for solving this problem, but the iterative processing times are subjectively defined, and it is hard to normally maintain good quality of every image after filtering. Moreover, if a corrupted image includes most high-frequency signals, then non-linear filtering techniques often make the wrong judgements and lose the original details, thus reducing the quality of the image. Even if the high-frequency signals are in a noise-free image, the well-known non-linear filtering techniques still filter this image and lose the original details. To solve this problem and improve the performance of the iterative non-linear filtering techniques, this paper proposes an

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automatic filtering convergence method using Peak Signal to Noise Ratio (PSNR) checking and filtered pixel detection.

The proposed automatic filtering convergence method consists of three parts. First, mean square error (MSE) is calculated to determine the similarity between the input image and the 1st filtered image. MSE equal to 0 indicates that the input image is the same as the 1st filtered image, and then the input image is unfiltered and becomes the output. Generally, PSNR performance improves and filtered pixels decrease as the iterative processing times increase for impulse noise reduction. Therefore, this study applies PSNR checking and filtered pixels detection to estimate the difference between the tth filtered image and the t–1th filtered image. Finally, in order to preserve the most original details of the images and remove the maximum amount of impulse noise, an adaptive and reasonable threshold is defined to make the iterative impulse noise filters proceed in finite steps.

The remainder of this paper is organized as follows: Section 2 introduces the related work about filtering impulse noise. Section 3 describes the proposed method. Section 4 shows experimental results using different test images with a series of impulse noise rations. Section 5 presents a discussion of the proposed method. Finally, the conclusions are in section 6.

2. Related work

The standard median filter is a classical non-linear filtering technique to remove impulse noise by the median pixel from the sorted pixels of a given working window (Arce & McLoughlin, 1987; Gabbouj, Coyle, Neal, & Callagher, 1992). The standard median filter usually loses the original details of an image and is not good for a corrupted image with a high-density level of noise. To overcome these limitations, the weighted median filter (WMF) (Yli-Harja, Astola, & Neuvo, 1991) and the center weighted median filter (CWMF) (Ko & Lee, 1991), which give more weight to the central pixel, are devised to improve the performance of the standard median filter. These two approaches reduce noise efficiently and reasonably for low-level noise, but they usually remove the details of the original image and create a distortion that induces those uncorrupted pixels to then be altered into highly corrupted images.

In order to avoid the above problem, a number of decision-based median filters (also called switching-based median filters) that combine noise reduction with noise detection have been proposed (Chen & Wu, 2001; Chen, Chen, & Chen, 2009; Chen, Ma, & Chen, 1999; Esakkirajan, Veerakumar, Subramanyam, & PremChand, 2011; Hosseini, Hessar, & Marvasti, 2015; Lin, 2011; Pok, Liu, & Nair, 2003; Sun & Neuvo, 1994; Zhang & Karim, 2002; Zhou, 2012). The multi-state median (MSM) filter (Chen & Wu, 2001) is adaptively switched among those of a group of center weighted median (CWM) filters (Ko & Lee, 1991) with varying center weights. The switching median (SM) filter (Zhang & Karim, 2002) is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators to filter impulse noise. The performances of MSM filter and SM filter are better than WMF and CWMF for impulse noise reduction in lowly corrupted images, but the filtered images retain a lot of noisy pixels with a high-density level of noise.

The noise detector of the conditional signal-adaptive median (CSAM) filter (Pok et al., 2003) performs iteratively in two stages: noise candidates are first selected using the homogeneity level, and then a refining process follows to eliminate false detections. Although the CSAM filter can strongly remove impulse noise, the content of filtered images will be blurred, reducing the quality of an image. The adaptive subband-based multi-state median (ASBMSM) filter (Chen et al., 2009) is proposed to overcome the above problem via Peak Signal to Noise Ratio (PSNR) checking.

There are two components in the ASBMSM filter: an image is divided into low-frequency and high-frequency blocks of size 8×8 by using DCT (discrete cosine transform), and then pixels in different blocks are filtered by the MSM filter using a working window of different sizes. A decision-based fuzzy (DFA) filter (Lin, 2011), consisting of a D-S (Dempster-Shafer) noise detector and a two-pass noise filtering technique, is presented. If the DFA filter detects a pixel corrupted with impulse noise, then a fuzzy averaging method is developed to achieve noise cancellation, and a second-pass filter is employed to improve the final filtering performance. The ASBMSM filter and DFA filter can only provide a good quality of an image with low-level density of noise, but they operate poorly in highly corrupted images.

A modified decision-based unsymmetrical trimmed median filter (ADBUTMF) algorithm (Esakkirajan et al., 2011) is proposed for the restoration of a highly corrupted image. There are two cases to replace the noisy pixel by ADBUTMF. If the selected window contains all the elements as noisy pixels, then the mean of these pixels is used for replacing the central pixel of the selected window; otherwise, the median value of the noise-free pixels is used for replacing the central pixel of the selected window. Zhou (2012) presents an adaptive detail-preserving filter based on the cloud model (CM) to remove impulse noise, called the CM filter. An uncertainty-based detector identifies the pixels corrupted by impulse noise, and then a weighted fuzzy mean filter is applied to remove the noise candidates. A two-step method (Hosseini et al., 2015) is proposed for real-time impulse noise suppression. The procedure examines the spatial correlation of suspicious pixels to decrease the false detection of uncorrupted pixels into being corrupted, and the noisy pixels are restored by using a weighted-average filter. This method, CM filter, and ADBUTMF all perform well for high-density level of noise, but they are only suitable for removing salt-and-pepper impulse noise.

For improving the performance of impulse noise reduction in highly corrupted images, decision-based median filters that detect noise and iteratively restore details of an image are proposed (Wang & Zhang, 1999; Luo, 2006; Ahmed & Das, 2014; Akkoul, Lédée, Leconge, & Harba, 2010; Dong & Xu, 2007; Xiong & Yin, 2012). Wang and Zhang (1999) propose a progressive switching medain (PSM) filter that judges whether the pixel is corrupted, according to either a very large value as a positive impulse noise or a very small value as a negative impulse noise, and then restores the corrupted pixel by a medain filter. The PSM filter is only proposed for salt-and-pepper impulse noise removal.

Luo (2006) presents an algorithm by using the alpha-trimmed mean in impulse noise detection instead of the pixel value estimation and by replacing the noisy pixels by a linear combination of their original value and the median of their local window. The directional weighted median (DWM) filter (Dong & Xu, 2007) is based on the differences between the current pixel and its neighbor pixels aligned in the horizontal, vertical, and two diagonal directions, and a directional weighted median filter is used to filter impulse noise. A new adaptive switching median (ASWM) filter (Akkoul et al., 2010) that improves the performance of the switching median (SWM) filter (Sun & Neuvo, 1994) is presented by computing the threshold locally from the image pixels' intensity values in a sliding window using weighted statistics. Xiong and Yin (2012) propose a noise removal method that measures how impulse-like each pixel is via the robust outlyingness ratio (ROR) value and divide these pixels into four clusters. The median of the absolute deviation in each cluster is then used to detect impulse noise. For filtering, the non-local means (NL-means) are extended to clean impulse noise.

Ahmed and Das (2014) present a salt-and-pepper impulse noise filter that operates in two stages: detection of noisy pixels with an adaptive fuzzy detector followed by denoising using a weighted