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Speedy filters for removing impulse noise based on an adaptive window observation

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ABSTRACT

A speedy filter for removing impulse noise based on an adaptive window observation is presented. The proposed method not only reduces specific content of impulse noise but also produces a low computational complexity in several noise densities, which exploits the adaptive concept. In this research, we use an adaptive window. It is a combination of the post filtered pixel and the pixel that would be filtered. Based on the adaptive window observation, we can get the output filter. The numerical results of using peak signal-to-noise ratio and computational time prove that the proposed method is able to reduce impulse noise and to produce a low computational complexity. Furthermore, the proposed method is capable of overcoming the drawback of previous studies and provides a satisfactory result.

1. Introduction

Noise often contaminates the digital image. One of the important tasks in image processing is to suppress impulse noise from digital images while keeping the original pixels intact [1]. A common noise problem in digital images is impulse noise. It is caused by the imperfection of camera sensors and communication channels, error in the data-acquisition system, interference from outside instrumentation, error in the transmission channel, etc. [2,3].

Impulse noise consists of irregular pulses that always degrade the quality of the image. A high-quality result for the image is important. One of the ways to produce a high-quality image despite a disturbance of impulse noise corruption is the use of a filtering process. It can reduce the noise in the contaminated image. The standard median filter is one of the most popular methods of removing impulse noise. It has a good denoising power and computational efficiency [4]. Several kinds of filtering methods have been proposed by adopting median filter theories, which include the relaxed median filter (RMF) [5]. The RMF provides a better noise removal and detail preservation [6]. However, results have blurring quality at high noise density. The progressive switching median filter (PSMF) is a derivative of the basic switching median filter [7]. The detection and removal of impulse noise in the PSMF are iteratively conducted in two separate stages. It has a very high computational complexity because of its iterative nature, which result in a long computing time process [8]. A detail-preserving filter for impulse noise removal based on the soft-switching median filter is called a detail preserving filter (DPF) [9]. The noise adaptive switching median-based filter (NASMBF) is a switching filter that identifies the noisy pixels and then corrects them by using a median filter [10]. However, the capability of both methods to reduce impulse noise is still not satisfying.

The recursive nonlinear filter using two conditional rules is presented in the fast impulsive noise removal (FINR) [11]. Meanwhile, the moving effect arises in the filtering results, which forms the smooth lines. The unsymmetrical trimmed variants detector (UTVD) uses an impulse detector based on the threshold value [12]. Furthermore, a decision-based scheme is presented in the decision-based algorithm (DBA) [13]. It removes high-density impulse noise effectively. However, the computation times of both methods to reduce impulse noise are still not good enough.

In previous research literature, many filtering methods are solely focused on reducing a specific content of impulse noise density and also need a long time for the filtering process. Several methods are only optimal to reduce high or small impulse noise density. To overcome the problem of the previous studies, a new method is proposed in this research paper. We present a speedy filter for removing impulse noise based on an adaptive window observation. Our method is focused on reducing not only a specific content of impulse noise density but also a wide-ranging variation

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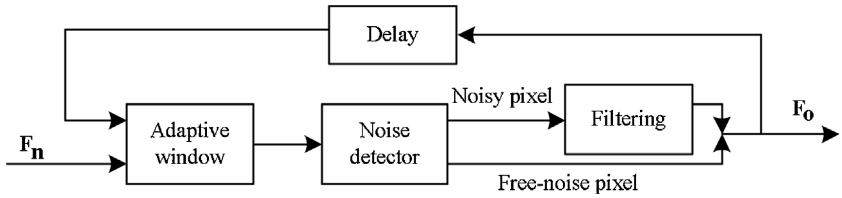

Fig. 1. Block diagram of the filtering process.

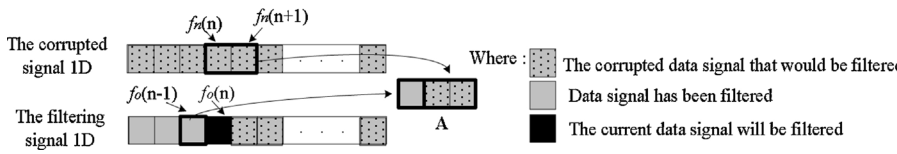

Fig. 2. One-dimension adaptive process in the 1 × 3 window size ($w(i)$).

of density. Impulse noise density can be expressed as the power of a signal. The higher impulse noise density will decrease the strength of an image signal and vice versa. We declare an impulse noise density in percent (%). In this case, the higher percentage of impulse noise density will have an impact on the greater density noise in the image, and vice versa. The proposed was tested on noise density ranging from 30% to 90%. In addition, the final filtering result produces a low computational complexity to get a fast computing time.

The paper is organized as follows: Section 2 covers the basic principles of the proposed method. Section 3 presents the experimental results. Finally, the conclusion is given in Section 4.

2. Proposed method

Our research paper introduces a new method for removing impulse noise by using adaptive techniques. The filtering process is only performed on the noisy pixel. Meanwhile, the noise-free pixel is not included in the filtering process. A block diagram of the filtering design is shown in Fig. 1. Our method has an input denoted as $\mathbf{F_n}$. Moreover, the output system is denoted as $\mathbf{F_o}$.

Referring to Fig. 1, it has a feedback from the output to the input. This feedback is used to update the pixel of $\mathbf{F_n}$ at the previous coordinates. Hence, the adaptive window contains pixels that have been filtered, and the pixel has not yet been filtered.

There are several blocks in Fig. 1, and these are adaptive windows, noise detector, filtering blocks, and delay. The detailed explanation in every block is described in the following subchapters.

2.1. Adaptive window

The filtering process often uses a discrete signal based on the window. The window contains data samples that will be used in the discrete filtering process. Meanwhile, the process of using a discrete filter consists of many variations of filtering methods. For example, there are average and median filters.

The adaptive window in the one-dimensional (1D) is filled with one data signal that has been filtered and two data from the corrupted signal, as shown in Fig. 2. The mathematical formula for collecting data samples is written in Eq. (1).

$$\mathbf{A} = |\, f_o(n-1) \quad f_n \quad f_n(n+1) | \tag{1}$$

$\mathbf{A}$ is an adaptive window in 1D. $f_o(n-1)$ is an element of 1D output signal. f_n and $f_n(n+1)$ are element of 1D input signal in current and previous position.

Fig. 3 is an adaptive window filtering process using the 3 × 3 window sizes in the two-dimensional (2-D) digital image. The adaptive window in the 2-D image takes the pixel that has been filtered and the pixel that would be filtered through to the 3 × 3 window. Eq. (2) shows the adaptive 3 × 3 window size. It contains nine pixels, from $f_o(x-1, y-1)$ up to $f_n(x+1, y+1)$. The image is scanned window by window (adaptive window). $\mathbf{W}$ is shifted one column to the right side from $f_o(x-1, y-1)$ up to $f_n(x+1, y+1)$, and then the window shifts from $f_o(x-1, y)$ up to $f_n(x+1, y+2)$.

$$\mathbf{W} = \begin{vmatrix} f_o(x-1, y-1) & f_o(x-1, y) & f_o(x-1, y+1) \\ f_o(x, y-1) & f_n(x, y) & f_n(x, y+1) \\ f_n(x+1, y-1) & f_n(x+1, y) & f_n(x+1, y+1) \end{vmatrix} \tag{2}$$

$\mathbf{W}$ is an adaptive window in 2D (3 × 3). $f_n(x, y)$ is element of image $\mathbf{F_n}$ and $f_o(x, y)$ is element of image $\mathbf{F_o}$.

2.2. Noise detector

We detect the noisy pixel using the absolute value of the difference between the median value (r_m) of an adaptive window ($\mathbf{W}$) and each element from $\mathbf{W}$, which is illustrated in Eq. (3).

$$d(i, j) = |\, r_m - w_{ij}| \tag{3}$$

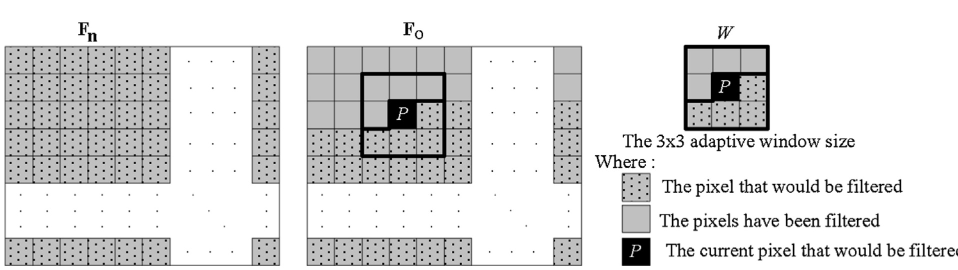

Fig. 3. The 3 × 3-adaptive window ($\mathbf{W}$) in the 2-dimension digital data.