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ScienceDirect
Signal Processing 87 (2007) 2017–2025
SIGNAL PROCESSING
www.elsevier.com/locate/sigpro

Impulse noise removal utilizing second-order difference analysis

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Received 3 November 2006; received in revised form 16 December 2006; accepted 20 January 2007
Available online 16 February 2007

Abstract

The pending problem that research in random-valued impulse noise filtering has been facing is the inability to distinguish noisy values that do not occur as extreme outliers in comparison with other surrounding pixels. In this paper, we propose a new detection and filtering algorithm that consists of (1) a two-stage detection scheme that employs second-order difference between pixels to determine the integrity of the image pixels and (2) a noise filtering process that estimates the original value of each noisy pixel utilizing the information gathered from (1). Due to its unbiased detection criteria, this method treats both fixed-valued and random-valued noise with extremely high detection rate.

Keywords: Image restoration; Impulse noise; Median filters; Noise detection

1. Introduction

Mechanical errors and environmental interference in noise-susceptible electronic equipments or communication channels lead to signal impurity [1]. In the case of capturing or transmitting image signal, this impurity can be classified into several types of image noise. Random occurrences of energy spikes of random amplitude generate impulse noise. Impulse noise can have fixed-value and random-value characteristics that both can be modeled as follows:

$$I(i,j) = \begin{cases} O(i,j) & \texttt{with probability } 1-\rho, \\ \xi(i,j) & \texttt{with probability } \rho, \end{cases} \quad (1)$$

where $O(i,j)$ and $I(i,j)$ denote the pixel values at location (i,j) of the original image and the noisy image, respectively, and ρ represents the noise ratio of the image. The term $\xi(i,j)$ denotes a noise value independent from $O(i,j)$ having equal probability $\rho/2$ of being either 0 or 255 in the case of fixed-valued impulse noise and having uniform distribution between 0 and 255 in the case of random-valued noise [2]. It should be mentioned that random bit errors also produce impulsive noise-like effects. The model of bit errors and other impulsive noise models are discussed in [3]. Both color images and gray-scale images can be contaminated by impulse noise. Several methods were proposed to restore the corrupted color images by using various vector filtering techniques in the literature [31–37]. In this paper, we will focus on gray-scale images and use the model described in Eq. (1), as practiced in [4–30]. Recent works [4–30] have used the fact that noisy values usually occur as extreme outliers when

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0165-1684/$ - see front matter
doi:10.1016/j.sigpro.2007.01.032

compared with other pixels. Upon the construction of a certain set of criteria or thresholds, separation of noise and original content could take place. However, the scenario becomes significantly more complex with random-valued noise. The difference between noise and image diminishes and sometimes becomes extremely difficult to detect.

Our proposed method aims directly at combating this issue. It does not only take into account extreme outliers but also evaluates the rate at which the differences between pixel values increase in order to detect sudden changes, one of the features that differentiate noise from the uncorrupted pixels. The proposed solution consists of two impulse detection stages and one noise filtering stage. The second impulse detection stage refines the findings from the first stage while the noise filtering process utilizes the refined detection results. The proposed algorithm exhibits better impulse noise removal ability than many other well-known methods, and requires no previous training. In particular, it can remove impulse noise from corrupted images very efficiently while preserving image details. The experimental results presented in this paper indicate that the proposed method performs significantly better than many other existing techniques.

The rest of the paper will lay out as follows. Section 2 briefly discusses difference analysis. Section 3 discovers the fundamental feature behind discriminating noise and discusses different noise detection methods implementing the discovered feature. Section 4 displays some of the extensive experimental results and finally Section 5 concludes the paper.

2. Difference analysis

Let us, first of all, define a few notations that will appear frequently in the paper. Let I denote the corrupted, noisy image of size $l_1 \times l_2$, and $I_{i,j}$ is its pixel value at position (i,j), i.e., $I = \{I_{i,j} : 1 \leqslant i \leqslant l_1, 1 \leqslant j \leqslant l_2\}$. Let $W(i,j)$ also denote a local window with the size of $(2K+1) \times (2K+1)$ such as:

$$W(i,j) = \{I(i-s, j-t) | -K \leqslant s \leqslant K, -K \leqslant t \leqslant K\}. \tag{2}$$

Let X consist of the pixels from $W(i,j)$ arranged in ascending order such that:

$$X_{(1)} \leqslant X_{(2)} \leqslant X_{(3)} \cdots \leqslant X_{((2K+1)^2)} \quad \texttt{where } X_{(k)} \in W(i,j). \tag{3}$$

During the noise detection process, the evaluation of the integrity of each pixel often utilizes the local window surrounding that pixel. One can observe that, statistically, the values of the local window pixels from the original image would form a certain range, $[R_{\min}, R_{\max}]$, with $R_{\min}$ being the minimum value and $R_{\max}$ being the maximum value of the local window. While homogeneous regions introduce a small range of $[R_{\min}, R_{\max}]$ and edge-like regions provide a larger range, this variation still stays remotely smaller than $[0, 255]$. Subsequently, the corruption process induces noise values that belong to three ranges: $[0, R_{\min})$, $[R_{\min}, R_{\max}]$, and $(R_{\max}, 255]$. Since the noise pixels in the middle group only slightly differ from the original pixels in values and have minimum effect on the overall quality of the image, noise detection pays greater attention to the other two groups of pixels, low-intensity and high-intensity noise. Among these pixel groups, the ownership of the currently examined pixel would reveal its integrity. Therefore, locating the boundaries that separate these two groups from the center group, $[R_{\min}, R_{\max}]$, enables such noise detection. These two groups require separate identification of each boundary due to the lack of correlation between them.

This incentive leads to the idea of dividing X at the median position as follows:

$$\begin{aligned} X_1 &= X_{(a)} && \texttt{where } 1 \leqslant a \leqslant [(2K+1)^2+1]/2, \\ X_2 &= X_{(b+[(2K+1)^2-1]/2)} && \texttt{where } 1 \leqslant b \leqslant [(2K+1)^2+1]/2. \end{aligned} \tag{4}$$

It is well known that a noisy pixel takes a gray value substantially larger than or smaller than those of its neighbors [11]. Therefore, the difference between noisy and noise-free pixels should significantly deviate from the differences between surrounding adjacent pixels. This would mark the location of the sought boundary between noisy and noise-free pixels. Hence, in each subset, let us calculate the difference between each pair of adjacent pixels and arrange the results in ascending order while mapping which difference belongs to which pair of adjacent pixels as follows:

$$\begin{aligned} &L = \texttt{sort}\ \{X_1(a) - X_1(a-1), \\ &2 \leqslant a \leqslant [(2K+1)^2+1]/2\}, \\ &U = \texttt{sort}\ \{X_2(b) - X_2(b-1), \\ &2 \leqslant b \leqslant [(2K+1)^2+1]/2\}. \end{aligned} \tag{5}$$