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Impulse noise suppression with an augmentation of ordered difference noise detector and an adaptive variational method

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ABSTRACT

In this letter, we propose an algorithm combining an impulse noise detector with a detail-preserving variational method for removing salt and pepper noise. Firstly, an impulse noise detector is presented, by augmenting the ordered difference of the current pixel value with other pixels' value in the sliding window to determine whether the current pixel is a noise pixel or not. Then, these noise pixels are restored using the variational method, which can preserve image edges and details. In the variation iteration process, an adaptive scheme of selecting neighbors of a noise candidate is proposed. As a result, noise free pixels remains and image details are preserved after applying our combined algorithm. Experiments for comparison indicate that the proposed algorithm is better than other impulse noise reduction methods in terms of noise removal and edge preservation.

1. Introduction

Many different filtering methods have been proposed for removing impulse noise, also known as salt and pepper noise, from digital images. A great majority of these methods are based on standard median filter (SMF) (Pitas and Venetsanopoulos, 1992) and its modifications (Brownrigg, 1984; Arce and Foster, 1989; Senel et al., 2002), which utilize the rank order information of the pixels contained in the filtering window. In (Ko and Lee, 1991), a center weighted median filter (CWM) giving more weight only to the center value in the filtering window was presented. In (Chen et al., 1999), a non-linear filter, called tri-state median filter (TSMF) combing the standard median filter (SMF) with the center weighted median (CWM) filter, was proposed for suppressing impulse noise. Adaptive center-weighted median filter (ACWMF) (Chen and Wu, 2001) gives the current pixel a large weight, and the final output is chosen between the median and the current pixel value. An impulse noise detection technique for switching median filters (ISM) was proposed in (Zhang and Karim, 2002), which is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators. Better noise removal methods with different kinds of noise detectors have been proposed, such as a detail-preserving median based filter (Sun and Neuvo, 1994), Jarque-Bera test based median filter (Dok and Yüksel, 2005), two-output non-linear filter (Russo, 2004), an efficient detail-preserving approach (EDPA) (Luo, 2006) and a neuro-fuzzy impulse detector (Yüksel and Besdok, 2004), use a noise detector to determine whether a pixel is a noise or not, and then the noise reduction process is only applied to noise pixels.

Methods mentioned above can achieve good results at low noise density but their denoising performances are unsatisfactory at high noise density. In (Weiyu and Jachen, 1997) minimum–maximum exclusive mean (MMEM) filter to remove salt and pepper noise from highly corrupted image was proposed. Recently, a detail-preserving variational method (DPVM) using smooth data-fitting term along with edge-preserving regularization has been proposed in (Nikolova, 2004) to reduce impulse noise. DPVM furnishes a new framework for the processing of image corrupted with impulse noise and preserves edges during the noise reduction. However, this method alters all pixels in the image, including those that are not corrupted by impulse noises and also has problem in detecting noisy patches. To avoid the drawback of DPVM method, in (Chan et al., 2005), a modified DPVM (MDPVM) method incorporating adaptive median filter (Hwang and Haddad, 1995) in the noise detection stage for salt and pepper noise reduction was proposed. This method only applies the detail-preserving variational method to noise pixels.

In this letter, we propose an impulse noise removal method combining an impulse noise detector with the detail-preserving variational method. Firstly, salt and pepper noise pixels are detected by the proposed noise detector. By augmenting ordered

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difference between the considered pixel and its neighbors in localized window we can make accurate impulse noise detection. And then these noise pixels are restored by the variational method. Neighbors of noise pixels are adaptively selected in our variational method. In (Nikolova, 2004; Chan et al., 2005), four neighbors of the noise pixel are used to calculate variation. It is likely that these four neighbors of a noise pixel are all noise pixels at high noise density. The usage of noise pixels may lead to distortion results. To avoid the effect of this phenomenon, in our first variation iteration process, noise free neighbors of a noise candidate are adaptively selected according to city-block distance between them and the considered noise pixel. Experiments show that the combined method has good performance in terms of subjective quality as well as objective quality in the result image than MDPVM.

The rest of the letter is organized as follows. Section 2.1 introduces our proposed detector for salt and pepper noise identification. The adaptive variational method is described in Section 2.2. Section 3 presents extensive simulation results. Finally, a conclusion is drawn in Section 4.

2. Impulse noise detector and the variational method

2.1. Impulse noise detection

Assuming any impulse noise corrupted image of size $m \times n$, and let y_{ij} be its pixel value at position (i,j), for $(i,j) \in I \equiv \{1,\ldots,m\} \times \{1,\ldots,n\}$. Let $W^y_{ij}(h)$ denote the window of size $(2h+1) \times (2h+1)$ centered about y_{ij}, i.e., $W^y_{ij}(h) = \{y_{i+k1,j+k2} | -h \leqslant k1, k2 \leqslant h\}$ is the set of points in $(2h+1) \times (2h+1)$ neighborhood centered at y_{ij} for some positive integer h. In the following discussion, let us only consider $h \geqslant 1$. We define $\Omega^0(p)$ as the set of points in $W^y_{ij}(h)$ deleted the center pixel p.

The intensity value of impulse pixel varies greatly from most or all of its neighboring pixels, whereas other pixels' neighbors composing pixels of similar intensity, even pixels on image details. So we can define relativity measure $d(p,q)$ in intensity of pixels between the center pixel p and its neighbors q_i as

$$d(p,q) = \sum_{k=\lfloor \tau \times T \rfloor}^{T} \exp(s_k), \tag{1}$$

where $\exp(x)$ is an exponent function, which is used to augment the ordered difference between the center pixel and its neighbors. The augmentation function $\exp(x)$ is such that the larger difference between the center pixel p and its neighbors is, the more highly it is augmented. In Eq. (1), $T = (2h+1) \times (2h+1) - 1, \tau$ is the trimming parameter and is assumed between 0 and 1, $\lfloor \cdot \rfloor$ is the floor function and s_k is the kth data item in the increasingly ordered samples of $|q_{(1)} - p| \leqslant |q_{(2)} - p| \leqslant \ldots \leqslant |q_{((2h+1)\times(2h+1)-1)} - p|$ $(q_i \in \Omega^0(p))$.

Therefore, we can get matrix $d_{ij}(p,q)$ of the whole image. We define an $m \times n$ zero flag matrix M and M_{ij} corresponding to y_{ij} is generated as follows,

Step 1: Divide the relativity measure matrix $d(p,q)$ into $g \times g$ blocks, which are neighboring, but do not overlap one another.

Step 2: Let *rms* be root mean square value of each $d(p,q)$ block. In each block, if $d_{ij}(p,q) > rms$, set $M_{ij} = 1$.

Step 3: If any pixel value y_{ij} in each block is equal to values of pixels which we mark in the step 2, set $M_{ij} = 1$.

The pixel y_{ij} is classified as a noise pixel if $M_{ij} = 1$; otherwise it is classified as a noise free one.

Since the noise detection plays a key role in the noise reduction, evaluation of the performance of the noise detection is necessary. In every noise image, let Ω_a denote a set of all actual corrupted pixels, Ω_d denote a set of pixels, which are detected as contaminated pixels by our proposed detector. Indices $E_1 = n_o/n_d$ and $E_2 = n_o/n_a$ are used to evaluate efficiency of detection, where n_o denotes the number of pixels in $\Omega_a \cap \Omega_d$, n_d is that of pixels in Ω_d, and n_a is that of pixels in Ω_a. We conduct experiments on 256-by-256 8-bit gray-scale peppers and camera images (Database) for a wide range of noise (salt and pepper) density levels – $10\% \leqslant p \leqslant 90\%$ with an increment step of 10%. $h = 2$, $\tau = 0.65$ and $g = 16$ are set in experiments. Test results are listed in Table 1. It is shown that our proposed detector can yield high performance even at high noise density.

Here, we investigate effects of the filtering window size $(2h+1) \times (2h+1)$, the block size g, and the trimming parameter τ in the noise detection stage on the performance of the proposed detector. The 256-by-256 peppers image is used in experiments. $h = 1,2,3,\ldots,10$ (with an increment step of 1; $g = 16$, $\tau = 0.65$), $g = 6,8,10,\ldots,24$ (with an increment step of 2; $h = 2$, $\tau = 0.65$) and $\tau = 0.40, 0.45, 0.50, \ldots, 0.85$ (with an increment step of 0.05; $h = 2$, $g = 16$) are tested for a wide range of noise density levels – $10\% \leqslant p \leqslant 90\%$ with an increment step of 20%.

Tables 2–4 present the performance comparisons. From these tables it is shown that the proposed method can get high performance when the parameter h is between 2 and 8, the parameter g is between 12 and 16 and the parameter τ is between 0.55 and 0.75. Whereas the larger the window parameter h is and the smaller the block size g is, the higher computation complexity is. So $h = 2$, $\tau = 0.65$ and $g = 16$ are set in experiments.

Next, the proposed noise detection algorithm is compared with the noise detection algorithms of ISM, ACWMF and MMEM methods. In these experiments, the test images are Bridge and Couple (Database), $h = 2$, $\tau = 0.65$ and $g = 16$ are set. Test results are listed in Table 5a and b. It is shown in the table that the proposed noise detection algorithm achieves much higher E_1 and E_2 values than ISM and ACWMF methods do. The proposed detector also outperforms MMEM method. Furthermore, the proposed detector can get 100% noise detection accuracy at some noise density.

The proposed detector for impulse noise ensures that almost all of the noise pixels are detected even at a high noise density. The noise pixels are restored by an adaptive variational method in the second stage, which we will discuss in the next section, while the remaining pixels are left unaltered.

2.2. Adaptive variation method for impulse noise removal

Signal and image restoration using convex cost-functions composed of a non-smooth data-fidelity term and a smooth regularization term is considered in the signal and image processing field for a long time. In order to restore image corrupted with impulsive noise, cost-functions composed of a data-fidelity term and an edge-preserving regularization term are provided. The minimizer

Table 1
E_1 and E_2 values of detection results after applying the proposed detector.

	Noise density (%)								
	10	20	30	40	50	60	70	80	90
Peppers									
E_1	1	1	1	1	1	1	1	1	0.9981
E_2	0.9979	1	1	1	1	1	1	1	1
Camera									
E_1	1	1	1	1	1	1	1	1	0.9999
E_2	1	1	1	1	1	1	1	1	0.9976