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An adaptive bilateral filter based framework for image denoising

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ABSTRACT

Conventional bilateral filter (BF) can suppress Gaussian noise effectively, but fail to remove impulsive noise and may blur edges in an image. To address these shortcomings, we aim to develop an improved bilateral filter based framework which is capable of effectively removing universal noise, i.e. impulses, Gaussian noise or mixture of the two types of noises, from images without oversmoothing edge details. To this end, our proposed denoising framework mainly consists of an impulse noise detector (IND), an edge connection precedure and an adaptive bilateral filter (ABF). Specifically, we first compute an edge component value to classify a pixel into impulse or nonimpulse. This is followed by an edge connection procedure, producing more connected edge regions. Then we introduce an adaptive bilateral filter which switches between Gaussian and impulse noise depending on the impulse noise detection results. This makes the adaptive bilateral filter be robust to these two types of noises. We also present an improved artificial bee colony (IABC) algorithm to optimize the parameters of the adaptive bilateral filter, enabling both effective noise removal and fine edge preservation. Experimental results demonstrate that the proposed image denoising framework outperforms alternative state of the art filters both in visual qualitative evaluations and quantitative comparisons.

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1. Introduction

Noise removal is an important preprocessing module for various image and video processing systems. The term *noise* in digital image processing is referred to any quantity that deflects an observed pixel from its raw value. Observed images can be easily corrupted by various noises in the process of acquisition or transmission. On the other hand, universal noise removal has always been a difficult problem. This is because the noises corrupting an image could be of various forms, such as additive Gaussian noise, impulse noise or multiplicative noise, with different characteristics.

Additive Gaussian noise is referred to quantities with a zero-mean Gaussian distribution and this type of noise could be added to images in the process of acquisition. Conventional linear filters remove Gaussian noises with detriments for edge and texture details in an image. To address this problem, a number of modified Gaussian noise removal methods have been studied for the purpose of edge-preserving [1–6]. Wavelet thresholding algorithm is one of the most favorable approaches. In wavelet thresholding frameworks, the notable BLS-GSM method [2] is adopted to adjust the neighborhoods of coefficients at different positions and scales and to apply the Bayesian least squares estimation technique to update the wavelet coefficients. In addition, the method SURE [3] considers Stein's unbiased risk estimate depending on the noisy image alone, so it is unnecessary to devise a specific statistical model for the wavelet coefficients. Though both the methods BLS-GSM and SURE prove to be effective in removing additive Gaussian noises in normal cases, their performances are hard to maintain when the Signal-to-Noise Ratios (SNRs) are reasonably low. Anisotropic diffusion (AD) [4] uses local conduction coefficients of the gradient magnitude function to preserve edges. However, AD is not appropriate for denoising images with texture structures, though the oversharpening and slow convergence issues may be addressed by some modified AD algorithms [5]. Buades et al. proposed an effective non-local means (NLM) filter [7] based on the similarities of local patches. However, this method suffers from high computational complexity in the global search for pixels with similar intensity. On the other hand, it does not perform well under low SNRs, even on the condition that several modified measures [8,9], such as the algorithm of principal neighborhood dictionaries for nonlocal means [8], have been exploited for alleviating the complexity of basic NLM. Bilateral filter (BF) [10] proposed by Tomasi and Manducci is another significant nonlinear filtering algorithm. BF uses local information of an image to identify detailed components and then smooth them less than the other components of the image. Moreover, this approach is simple, noniterative and local [10,11]. One of the most limitations of BF is that the range filter coefficients rely heavily on pixel intensity values. Furthermore, BF does not consider edge

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information, and thus cannot balance the effects of noise removal and edge preservation. Several algorithms of BF have been proposed to address visual details and smooth the rest regions as much as possible [12–16]. On the other hand, BF is a class of Gaussian noise removal methods with parameters which are usually determined by trial and error in practice. Fixed parameters may not be well suited for noise removal and edge preservation for all regions within an image. In [16], Zhang et al. proposed that a good range for the standard deviation of the domain filter is rough [1.5–2.1], and the optimal standard deviation of the range filter changes importantly as the noise standard deviation changes. Yang et al. utilizes particle swarm optimization (PSO) algorithm to adjust the parameter of BF [17]. However, it does not explain the details about how to choose the fitness function and the parameter values of PSO. Above all, there are seldom theoretical insights into the problem of how to obtain the optimal values for the parameters of BF.

Another type of noise often corrupting an image is impulse noise, which replaces the values of a portion of pixel with random values. Such noise will exist in an image due to transmission errors [18]. Median filter can remove impulse noise to a certain extent, with some of its improved alternatives better preserving edge and details [19–23]. For instance, the adaptive center-weighted median filter (ACWMF) [19] incorporates an adaptive threshold into the center weighted medians for detection. ACWMF can remove impulse noise much more effectively for low level noise, but its denoising performance is not satisfactory under low SNRs. The directional weighted median (DWM) filter [20] is another impulse noise suppression method with a detector on account of absolute differences within the filtering window. For upgrading high accuracy of detection, DWM filter needs to iterate, and thus takes a longer processing time. Another solution for impulse suppression is that the switching procedure detects impulse pixels before filtering and replaces them with estimated values while leaving the remaining pixels unchanged [24,25]. The switching algorithms blur fewer pixels than other global pixels processing methods, and thus could more or less preserve details along edges in an image.

In practice, mixed noise including the Gaussian and impulse noise could occur simultaneously during the transmission and acquisition. A number of attempts have been made to remove mixed noise from images [26–32]. The median-based signal-dependent rank ordered mean (SD-ROM) filter [26] claims the capability of removing impulse noise and mixed noise as well. Trilateral filter (TF) [28] and switching bilateral filter (SBF) [29] are also two notable filters on the basis of BF for removing mixed noise in gray images. TF computes the rank-order absolute difference (ROAD) statistics for impulse noise detection. SBF proposed the sorted quadrant median vector (SQMV) scheme for detecting impulse noise, and the range filter inside the BF switches between Gaussian and impulse noise relying on the noise classification results. By and large, SD-ROM, TF and SBF all can suppress mixed noise to a certain extent under reasonable SNRs. However, experiments show that they are incapable of denoising an image which is heavily corrupted by mixed noise. Therefore, a mixed noise removal method for low SNR images is needed.

In this paper, we present an image denoising framework based on an impulse noise detector and a modified BF with adaptive parameters. We particularly apply the framework to the task of removing impulse noise and Gaussian noise simultaneously. It employs the edge component [33] variation between the current pixel and its neighbors to detect impulse noise. Moreover, the edge component is also exploited as connections for discontinuous edges. BF plays a role of suppressing Gaussian and impulse noise. In order to preserve edge structures and reduce noise in smooth regions, an improved artificial bee colony (IABC) algorithm is proposed to optimize the parameters of BF, in which the best direction is obtained to modify the search process and the search range for the scout bee is reduced. The proposed framework generalizes classical bilateral filters from addressing Gaussian noise to mixed noise consisting of both impulse and Gaussian noise.

This paper is organized as follows. In Section 2, we briefly review the image model, the conventional bilateral filter, the anisotropic Gauss filter and the artificial bee colony algorithm. Section 3 presents the impulse noise detection scheme, edge connection measure and the BF optimized by the IABC algorithm. In Section 4, we demonstrate the experimental results on impulse and Gaussian noise removal. Finally, Section 5 concludes our work.

2. Fundamentals

2.1. Noise models

We represent an image in terms of a matrix $\boldsymbol{Y}$ with the entry $y_{m,n}$ denoting the intensity value of the pixel at (m,n).

Provided that an image is corrupted by additive Gaussian noise as follows:

$$y_{m,n} = o_{m,n} + z_{m,n} \tag{1}$$

where $o_{m,n}$ denotes the pixel intensity of a noise-free image $\boldsymbol{O}$ at (m,n) and $z_{m,n}$ is the added noise value produced from a zero-mean Gaussian distribution.

For the case of impulse noise, a portion of original pixel values are replaced by random values drawn from some distribution. Let $z_{m,n}$ denote the intensity value of impulse noise at (m,n). $z_{m,n}$ is between maximum intensity value $I_{\max}$ and minimum intensity value $I_{\min}$. If $z_{m,n}$ only defines either $I_{\max}$ or $I_{\min}$, the noise model is referred to as salt-and-pepper noise. Furthermore, on condition that $z_{m,n}$ takes random values from the interval $[I_{\min}, I_{\max}]$ with a uniform distribution, the noise model is referred to as uniform impulse noise. The impulse noisy image can be expressed as

$$y_{m,n} = \begin{cases} z_{m,n} & \text{with probability } p \\ o_{m,n} & \text{with probability}(1-p) \end{cases} \tag{2}$$

where p denotes the probability of a noise-free image corrupted by impulse noise.

2.2. Bilateral filter

Processing a noisy image $\boldsymbol{Y}$ through bilateral filtering can be formulated as follows [10]:

$$\hat{o}_{m,n} = \sum_{p=m-R}^{m+R} \sum_{q=n-R}^{n+R} H(m,n;p,q) y_{p,q} \quad \forall (p,q) \in \Omega_{m,n}^{R} \tag{3}$$

where $\hat{o}_{m,n}$ denotes the processed pixel at (m,n), $H(m,n;p,q)$ is the weight coefficient between the current pixel and its neighboring points, and $\Omega_{m,n}^{R}$ represents a set of pixels in a $(2R+1) \times (2R+1)$ window centered on (m,n). The weight coefficient is given by [10]

$$H(m,n;p,q) = \begin{cases} w_{m,n}^{-1} \exp\left(-\frac{(p-m)^2+(q-n)^2}{2\sigma_d^2}\right) \exp\left(-\frac{(y_{p,q}-y_{m,n})^2}{2\sigma_r^2}\right) & \text{if } (p,q) \in \Omega_{m,n}^{R} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where σ_d and σ_r are the standard deviations of the domain and range Gaussian filters, respectively. $w_{m,n}$ is a normalization factor to make the filter preserve an average gray value in constant of the

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