J. Vis. Commun. Image R. 38 (2016) 440–450

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Iterative non-local means filter for salt and pepper noise removal ☆

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ARTICLE INFO

Article history:
Received 26 November 2015
Revised 28 February 2016
Accepted 27 March 2016
Available online 31 March 2016

Keywords:
Salt and pepper noise removal
Non-local means
Iterative filtering

ABSTRACT

Salt and Pepper noise (S&P noise) removal is an active research area in digital image processing. Existing techniques commonly use the local statistics within a neighborhood to estimate the centered noisy pixel, and tend to damage image details due to the image local diversity singularity and non-stationarity. To address this problem, in this paper, iterative nonlocal means filter (INLM) is proposed to exploit the image non-local similarity feature in the S&P noise removal procedure. Moreover, the proposed iterative framework update the similarity weights and the estimated values for higher accuracy. The experimental results show that the proposed INLM produces better results than state-of-art methods over a wide range of scenes both subjectively and objectively, and it is robust to the detection results.

1. Introduction

Digital images are usually contaminated by S&P noise which is introduced during image acquisition, transmission and recording process. S&P noise ruins image signal in terms of short-duration, discontinuous, noise spikes, which severely affects the subsequent image processing operations. Hence, S&P noise removal is crucial in digital image processing.

Many filtering techniques had been proposed for this specific problem. The most popular and robust nonlinear filters were median filter (MF) [1] and its variations [2–4]. However, these kinds of filters treated all pixels with the same manner and replaced all the noise free pixels with the estimated values. As the result, the details of the image would be damaged, especially in the case of low signal noise ratio (SNR). To avoid this situation, various switching based filters, which introduced noise detection process before image restoration were proposed, such as [5–21]. Among these techniques, boundary discriminative noise detection filter (BDND) [12], modified BDND (MBDND) [13] and the sorted switching median filter (SSMF) [21] achieved widely acknowledged for the abilities of protecting the image detail information. Another kinds of methods were committing to find more effective filters. Yuksel [22], Toh and Isa [23], and Civicioglu [24] introduced a kind of hybrid filters, which combined median filter with other process, such as edge detector and neuro-fuzzy network in the denoising procedure, Morillas et al. [25], Camarena et al. [26], Morillas et al. [27], Smolka and Chydzinski [28], and Smolka [29]used peer group filters and fuzzy metrics for color images denoising. Recently, to get better denoising effect, many methods had been proposed based on a kind of new ideas that took full advantage of the different characteristics of the image and noise, and obtained a good denoising effect. For example, Zuo et al. [30] introduced a denoising procedure based on noise space characteristic, Zhang and Xiong [15] used image directional difference detector on the basis of adaptive weighted mean filter (SAWM). Zhou [31] proposed a novel effective filter based on the cloud modeling (CM) which used the uncertainties of the noise. By taking different kinds of characteristic into account, these kinds of filters restored the image with better performance and achieved wide acception.

Although existing techniques have been widely accepted and achieved lots of remarkable results, there is still much room for improvement. Classic techniques in image S&P noise removal strongly rely on exploiting information in a local window around the estimated pixel for this specific restoration task. However, considering the diversity singularity and nonstationary feature of the image signal in a local window, the estimation result could easily diverge from the true value and cause ugly visual effects in texture and edge regions, especially in the case of high noise density. Therefore, local information is insufficient for high quality image restoration. It has been proved and widely accepted that one can expect better denoising performance by exploiting the nonlocal information of the image signal in the case of gaussian distributed noise suppression [32,33]. This inspired us that can we achieve better restoration performance in S&P noise removal by exploiting image non-local information during the denoising procedure? In

☆ This paper has been recommended for acceptance by Hongliang Li.

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http://dx.doi.org/10.1016/j.jvcir.2016.03.024
1047-3203/

this paper we will discuss this question and propose an iterative nonlocal means filter (INLM) for image S&P noise removal. The concept of nonlocal means filter (NLM) is based on the fact that there exists lots of similar patches with repeat patterns in natural images, and the central pixels of these similar patches share the same gray value distribution. Instead of estimating the pixel value within a local window, NLM replaces the considered pixel by the weighted mean of all the similar patterns' central pixels. NLM has been widely accepted in image Gaussian noise suppression, however, its application in S&P noise removal has been barely discussed. In this paper, we will integrate the NLM algorithm into a S&P noise removal problem. Moreover, an iterative weighted average scheme is carried out and an iterative nonlocal means filter is proposed for further improvement. The simulation results show that the proposed INLM is capable of recovering image fine details and textures reliably at a wide range of S&P noise densities so that it outperforms other state-of-art denoising methods in terms of both subjective and objective qualities.

The outline of this paper is organized as follows. In Section 2, we analyze the characteristics of both Gaussian noise and S&P noise, and explain why the NLM algorithm for Gaussian noise filtering can be integrated into a S&P noise suppression problem. In Section 3, we will develop the proposed INLM for S&P noise removal in three stages. In Section 4, experimental results of our method and a comparison study with some state-of-art techniques are presented. Finally, we conclude the paper in Section 5.

2. Noise models and NLM for image denoising

2.1. Noise model analysis

In the process of image acquisition, transmission and storage, different mechanisms would introduce different types of noise. The two most common noise models are Gaussian noise and S&P noise.

Gaussian noise is a kind of additive noise whose amplitude obeys Gaussian distribution as follows:

$$p(n) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(n-\mu)^2}{2\sigma^2}}, \tag{1}$$

where n denotes the noise value, μ and σ denote the noise mean and standard deviation respectively.

S&P noise is another commonly encountered noise type which appears as black and white spots randomly distributed over the image. When an image is corrupted by S&P noise, only a certain portion of the image pixels are replaced with noise values while the remaining pixels are unchanged. In this case, the values of the noisy pixels have either maximum value (r_{max}) or minimum value (r_{min}) of the image intensity range. The S&P noise model with probability ρ can be defined as follows:

$$X(i,j) = \begin{cases} r_{max}, & \textit{with probability } a \\ r_{min}, & \textit{with probability } b \\ x(i,j), & \textit{with probability } 1-\rho \end{cases}, \tag{2}$$

where $X(i,j)$ denotes the luminance values of the noisy image at the location (i,j), and $x(i,j)$ denotes noise-free pixel values at the location (i,j) with probability $1-\rho$, and $a+b=\rho$.

For further analysis, we visualize the histogram of those noise model and their influence on a clear image. Fig. 1(a) shows a histogram image of a testing image *Lena*. Fig. 1(b) and (c) are the histogram of noised image contaminated by S&P noise and Gaussian noise respectively. In Fig. 1(b), S&P noise falls into the red[1] rectangle. And the histogram of Gaussian noise is given in Fig. 1(d).

The amplitude and distribution characteristics of these two kinds of noise are so different that the processing methods on these two kinds of noise in principle are also different from each other. However, it occurs to us that what is the amplitude and distribution characteristic of S&P noise after prefiltering? To find out the answer to this question, we implemented switching based median filter (SMF, introduced in Section 3, Part 1) on S&P noised images and analyzed the histogram of the noisy pixels after filtering. An example of the noise histogram of *Lena* is given in Fig. 2(a). In this example, the testing image corrupted by S&P noise with different noise densities was filtered by SMF. The noise histogram after prefiltering is represented by green curves in Fig. 2(a). The red line in the figure represents the Gaussian distribution curve. We find that the noise histogram of each pre-filtered image approximately obeys Gaussian distribution. To make the discovery more convincing, we tested a bunch of images and showed the noise histogram after prefiltering in Fig. 2(b). It can be seen that the green curves are all very close to the red curve, which means that after SMF, the model of the noise remained in the image is very close to Gaussian distribution. This inspires us that can we achieve better recovering denoising performance by successfully fitting a Gaussian noise filter into an impulse noise removal problem? In this paper, we will discuss about this question and give an affirmative answer by applying NLM filter into S&P noise removal.

2.2. NLM algorithm for Gaussian noise filtering

The NLM algorithm was proposed to process images contaminated by Gaussian noise. For each pixel to be estimated, the NLM takes into consideration the similarity between the neighborhood configuration of this pixel and all the pixels in every neighborhood. Mathematically, the estimated pixel $\hat{X}_{i,j}$ can be computed as a weighted average of all the neighborhood pixels in the noisy image as follows:

$$\hat{X}_{i,j} = \frac{\sum_{k,l \in \Omega_{i,j}} w_{i,j,k,l} Y_{k,l}}{\sum_{k,l \in \Omega_{i,j}} w_{i,j,k,l}}, \tag{3}$$

where $\Omega_{i,j}$ is the patch group similar to the current patch centered by $\hat{X}_{i,j}$, $Y_{k,l}$ is the center pixel of the similar patches in $\Omega_{i,j}$. The candidates in $\Omega_{i,j}$ are similar patches whose Euclidean distance is close enough to the current patch centered by $X_{i,j}$. In Eq. (3), weights $w_{i,j,k,l}$ defines the weight for each candidate $Y_{k,l}$, which can be calculated as follows:

$$w_{i,j,k,l} = e^{\frac{\|P(X_{i,j})-P(Y_{k,l})\|_{2,a}^2}{h^2}}, \tag{4}$$

where $P(X_{i,j})$ and $P(Y_{k,l})$ represent the local windows centered by pixel $X_{i,j}$ and $Y_{k,l}$ in the noised image. And h is the smoothing parameter, which controls the decay of the exponential function. The norm used in Eq. (4) is simply the Euclidean difference, weighted by Gaussian kernel of zero mean and variance a.

NLM has achieved satisfactory performance in Gaussian noise suppression because during denoising, not only local statistical information but also global structure similarity are taken into consideration. However, it could not be implemented in S&P noise removal directly because pixels corrupted by S&P noise are significantly different from their neighbors. This will lead to significant mistakes during similarity weights calculation. To solve this problem, in this paper, a new framework is constructed. The S&P noise are first pre-filtered via statistical filter and then NLM is implemented on noised pixels iteratively to refine the denoising results.

[1] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.