J. Vis. Commun. Image R. 36 (2016) 1–10

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

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

A neutrosophic filter for high-density Salt and Pepper noise based on pixel-wise adaptive smoothing parameter ☆

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ARTICLE INFO

Article history:
Received 2 January 2015
Accepted 6 January 2016
Available online 11 January 2016

Keywords:
Image denoising
Salt and Pepper noise
Adaptive neutrosophic weight function
Pixel-wise adaptive smoothing parameter
Indicator of image contents
Similarity measurement
Neutrosophic Set
Indeterminacy

ABSTRACT

Image indeterminacy has been neglected in most traditional filtering algorithms. This paper proposes a pixel-wise adaptive neutrosophic filter based on neutrosophic indeterminacy feature to remove high-level Salt-and-Pepper noise. In the proposed algorithm, the indeterminacy of a pixel is quantified by a Neutrosophic Set and innovatively exploited as an efficient characteristic of measuring the similarity of pixels. In order to adjust the smoothing parameter of the weight function pixel-wise adaptively, the uncertainty of a pixel is utilized as an indicator of image contents. Extensive experiments on numerous images demonstrate that with a 3×3 window, our method outperforms many existing denoising methods in terms of noise suppression and detail preservation.

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1. Introduction

Noise is an unwanted signal that corrupts the original image in various processes such as image acquisition, transmission and storage. The aim of image denoising is to remove noise while retaining useful details as much as possible. One of the most destructive noises is Salt-and-Pepper noise (SPN) that replaces the original pixels with the maximum or minimum gray level of the image. Quality of the original image is deteriorated significantly, so it is imperative to eliminate noise before subsequent image processing, such as object recognition and image segmentation.

Numerous methods have been proposed to remove SPN. The most popular nonlinear filter is the median filter (MF) [1], but strong, undesired contouring effect is produced by MF. It performs well only in low-density noise and under high-density (>70%) environment [2], a larger window size can improve the performance of noise removal; however, it makes a looser correlation between the median value and the corrupted pixel, which leads to the blurring of image details [2,3]. Furthermore, the most appropriate window size varies with the density of noise, so it is rather difficult to choose the optimal one. To automatically adjust the window size, an adaptive median filter (AMF) has been put forward in [4,5], but at high noise density (HND), the biggest template size has reached 39×39, and the computation is exceedingly heavy. Another drawback of MF is that it executes identically on all pixels in the image, yet an ideal filter should be applied only to noisy pixels while leaving noise-free pixels intact. Hence, a switching median filter (SMF) [6] was introduced to avoid the injuring of uncontaminated pixels. In SMF, noisy pixels are firstly identified by certain strategies and then removed by specialized regularizations. There are some well-known methods with the switching scheme, such as decision-based algorithm (DBA) [7], switching-based adaptive weighted median (SAWM) [8], modified decision based unsymmetrical trimmed median filter (MDBUTM) [9], fuzzy-based decision algorithm (FBDA) [10], and decision-based trimmed median filter (DBTMF) [11]. In DBA, if a pixel has a gray value of 0 or 255 in 8-bit image, it is considered to be a noise candidate. In noise reduction stage, the noise candidate is replaced by the median value as long as at least one noise-free pixel exists in the 3×3 window, otherwise it will be replaced by its neighborhood pixels. Nevertheless, this kind of repetitive replacement results in annoying artifacts in HND. To overcome this problem, when all pixels are contaminated, MDBUTMF substitutes the mean value of all noisy elements in the filtering template for the center pixel, which generates artificial spots in the restored image. It is clear that the drawback common to DBA and MDBUTMF is that they all ignore the correlation between pixels. In FBDA, the

☆ This paper has been recommended for acceptance by Yehoshua Zeevi.

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http://dx.doi.org/10.1016/j.jvcir.2016.01.005
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maximum and minimum of window gray value are regarded as noisy points, and the pixels similar to these polluted ones are all eliminated by a fuzzy mechanism. Then the median of the remaining elements is exploited to refresh the center pixel. The strategy of DBTMF is similar to that of FBDA and the only difference between them is that the median value is computed after eliminating pixels with the value of 0 or 255. The major disadvantage of these extreme-compression methods is that only the high reliability of the median is considered while the local information of pixels has been neglected. Consequently, details and edges cannot be recovered satisfactorily. In order to overcome this shortcoming, the theory of image inpainting has been introduced to preserve edges. In [12,13], a three-stage filter (TSF) and an adaptive iterative convolutions filter (ACIF) have been proposed, respectively. They can not only suppress noise, but also preserve edge information efficiently. However, on account of iterative inpainting, the phenomenon of undue blurring or over-smoothing is obvious in the restored image at HND. In non-local means (NLM) [14,15] filter, a weighting scheme is applied, where the weight is determined by the similarity of local patches. NLM is powerful against Gaussian noise, but performs poor in SPN. Besides, in the weight functions of most NLM filters, the value of the smoothing parameter h is usually set manually. Methods for adaptive h have been studied [15,16], but on account of having not taken image contents into consideration, most algorithms still use a globally constant value of h.

Due to the complexity of noise sources and the imperfection of certain definitions, such factors as ambiguity, vagueness and imprecision are widespread in image processing. Nevertheless, algorithms above-mentioned have not taken them into account. Unlike conventional algorithms, in [17], the indeterminacy information is introduced to image denoising and a Neutrosophic entropy filter (NEF) has been presented. In NEF, the contaminated image is transformed into Neutrosophic Set (NS) domain at first, then an iterative γ-median filtering is applied to reduce the indetermination degree evaluated by neutrosophic entropy. It can remove different kinds of noises effectively, but the iterative operation of γ-median generates undue blurring of images. At present, Neutrosophy has been used not only in image denoising but also in image segmentation [18,19]. Consequently, how to further maximize the potential of indeterminacy in image restoration is a meaningful task.

In this paper, by exploiting the indeterminacy information based on NS, a new powerful neutrosophic filter is presented for the reduction of high density SPN. On one hand, the uncertainty of a pixel is regarded as a feature of measuring pixel similarity; on the other hand, by using the indeterminate information to distinguish the regional type to which a pixel belongs, a pixel-wise adaptive smoothing function is put forward to minimize the negative influence resulting from a globally fixed h. Experimental results on a series of images have demonstrated that the proposed adaptive neutrosophic weighted filter (ANWF) outperforms the counterparts in terms of visual quality and objective performance.

The outline of the paper is organized as follows. NS and the quantification of uncertainty are briefly introduced in Section 2. Section 3 describes ANWF in detail. Results of the proposed algorithm are described and discussed in Section 4. Section 5 concludes the paper.

2. Quantification of indeterminacy

2.1. Neutrosophic Set

Proposed by Florentine Smarandache, Neutrosophy is the foundation of neutrosophic logic, neutrosophic statistics, Neutrosophic Set and neutrosophic probability [20,21]. In neutrosophic logic, ⟨A⟩ is a theory, entity or event, and ⟨Anti-A⟩ is the opposite of ⟨A⟩. A new concept ⟨Neut-A⟩ is introduced to express the case of neither ⟨A⟩ nor ⟨Anti-A⟩ and used to describe the indeterminacy of an event [21]. For example, if ⟨A⟩ = black, then ⟨Anti-A⟩ = white, ⟨Neut-A⟩ = red, green, purple, cyan, blue, yellow, etc. (any color except white and black). In the contaminated image, sometimes it is difficult to distinguish whether a pixel is noisy or noise-free due to the existing of textures or boundaries. In this paper, we denote the background of image as ⟨A⟩, the edge or texture as ⟨Neut-A⟩, and noise as ⟨Anti-A⟩. Three neutrosophic components denoted by T, I and F are applied to estimate the degrees of truth, indeterminacy and false, respectively. Let T, I and F be non-standard or standard real subsets of $]{-0},1{+}[$ with $\sup T = t\_\sup$, $\inf T = t\_\inf$, $\sup I = i\_\sup$, $\inf I = i\_\inf$, $\sup F = f\_\sup$, $\inf F = f\_\inf$, and $n\_\sup = t\_\sup + i\_\sup + f\_\sup$, $n\_\inf = t\_\inf + i\_\inf + f\_\inf$ [29]. Where $x\_\sup$ and $x\_\inf$ are the superior and inferior limits of subset x. There are no restriction on $n\_\sup$ *and* $n\_\inf$, so $^{-}0 \leqslant n\_\sup \leqslant 3^{+}$ and $^{-}0 \leqslant n\_\inf \leqslant 3^{+}$. T, I and F can be any real sub-unitary subsets and are not necessarily intervals. Besides, the three sets may overlap or be converted from one to the other [30]. An element A (t, i, f) belongs to the set in the following way: it is t true ($t \in T$), i indeterminate ($i \in I$), and f false ($f \in F$). In Neutrosophy, if an event ⟨A⟩ is t % true, it does not necessarily mean it is $(1-t)$ % false, but can be f % false and i % indeterminate simultaneously. However, in traditional logic, if an event ⟨A⟩ is t % true, it must be $(1-t)$ % false.

2.2. Neutrosophic image

In neutrosophic domain, a neutrosophic image P_{NS} is represented by three sets I, T and F [19], and a neutrosophic pixel is denoted as $P(t,i,f)$. The expression of neutrosophic pixel signifies the point is t % true (background), i % indeterminate (texture or edge) and f % false (noise), where i varies in I, t varies in T, and f varies in F, respectively. A pixel $P(i,j)$ in traditional image can be transformed into neutrosophic domain in the following way: $P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\}$. In order to make full use of the uncertain information to restore the corrupted image, an efficient estimation of I is critical. It is well known that the median value has stronger immunity to SPN, so it can be used to construct the function of I. Besides, the maximum absolute luminance difference defined as Eqs. (1) and (2) can reflect the distinction between the center pixel and its neighboring pixels, hence it can be utilized to evaluate the degree of current pixel being noise-free.

$$Dif(i,j) = \max\{dif(i+k,j+l)\}, \tag{1}$$

$$dif(i+k,j+l) = |p(i+k,j+l) - p(i,j)| \quad with\ (i+k,j+l) \neq (i,j), \tag{2}$$

Motivated by Ref. [17], $I(i,j)$, $T(i,j)$ and $F(i,j)$ are formulated as

$$I(i,j) = \frac{\delta(i,j) - \delta_{\min}}{\delta_{\max} - \delta_{\min}}, \tag{3}$$

$$\delta(i,j) = |P(i,j) - m(i,j)|, \tag{4}$$

$$m(i,j) = median\begin{bmatrix} p(i-1,j-1) & p(i-1,j) & p(i-1,j+1) \\ p(i,j-1) & p(i,j) & p(i,j+1) \\ p(i+1,j-1) & p(i+1,j) & p(i+1,j+1) \end{bmatrix}, \tag{5}$$

$$T(i,j) = \frac{Dif_{\max} - Dif(i,j)}{Dif_{\max} - Dif_{\min}}, \tag{6}$$

$$F(i,j) = 1 - T(i,j). \tag{7}$$

where $m(i,j)$ is the local median value of the $w \times w$ window ($w = 2n+1$ $(n \geqslant 1)$) centered at (i,j), and in a 3×3 window, it

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