Computer Standards & Interfaces 36 (2014) 631–640

Contents lists available at ScienceDirect

Computer Standards & Interfaces

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

Partition-based fuzzy median filter based on adaptive resonance theory

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ARTICLE INFO

Article history:
Received 3 October 2012
Received in revised form 5 September 2013
Accepted 10 September 2013
Available online 18 September 2013

Keywords:
Impulsive noise
Fuzzy rule
Adaptive resonance theory
Median filter
Least mean square

ABSTRACT

This paper presents a novel partition-based fuzzy median filter for noise removal from corrupted digital images. The proposed filter is obtained as the weighted sum of the current pixel value and the output of the median filter, where the weight is set by using fuzzy rules concerning the state of the input signal sequence to indicate to what extent the pixel is considered to be noise. Based on the adaptive resonance theory, the authors developed a neural network model and created a new weight function where the neural network model is employed to partition the observation vector. In this framework, each observation vector is mapped to one of the M blocks that form the observation vector space. The least mean square (LMS) algorithm is applied to obtain the optimal weight for each block. Experiment results have confirmed the high performance of the proposed filter in efficiently removing impulsive noise and Gaussian noise.

1. Introduction

Digital image processing technologies of all kinds have been pervasively utilized in various professional areas such as geographical analysis, diagnostic imaging, image-based control and instrumentation, etc. so as to enhance the quality of common people's lives. The performance of image processing tasks such as edge detection, image retrieval, and image segmentation strictly depends on the quality of the digital images input. Unfortunately, due to a number of imperfections in the imaging process, recorded images are often contaminated by impulsive noise during image acquisition or transmission. Noise is usually caused by either a faulty imaging system (i.e., sensor noise) or an imperfect medium (i.e., random scattering and absorption) [12,27], both happening every now and then. Therefore, the removal of noise from digital images has received a lot of research interest in the last decade. However, methods currently available for the restoration of digital images corrupted by noise unfortunately introduce undesirable blurring effects [30].

Based on order statistics, the median filter and its derivatives have shown good efficiency in suppressing impulsive noise [3,4,9,13,15–19,25,27,29,31,36,41]. However, these approaches are location-invariant in nature, which can easily bring significant blurring effects into the image details. Recently, to avoid modifying noise-free pixels, decision-based median filters with thresholding operations have been developed [10,11,21,28,32,33,35,37,38]. They mainly employ a decision-making mechanism to determine whether the input pixel to a given filtering window is noisy. After the noise filtering operation, only the pixels which are identified as corrupted by the decision-making mechanism are processed. Pixels that are classified as noise-free are left unchanged. These methods enhance the noise removal performance and reduce the distortion effects. However, one disadvantage of these hard switching schemes is that they have trouble exploiting fixed decision-making processes since the threshold parameters are obtained at a pre-assumed noise density level. To remedy the problem, Lin and Yu thus proposed their adaptive two-pass median filter (ATM) based on support vector machines (SVM) [22]. Additionally, Tsai, Chang, and Lin introduced such concepts as decision tree, particle swarm optimization, as well as SVM and designed a median-type filter [43]. These filters can enhance the noise removal performance and reduce the distortion effects.

Alternatively, some filtering methods for the removal of noise from digital images use neural-fuzzy systems [1]. Neural-fuzzy median filters are controlled by fuzzy rules that judge the possibility of the existence of impulsive noise. Neural-fuzzy median filters are designed in a way that they can be trained over a reference image and yield weighting coefficients. It is thus not necessary to obtain any membership functions to represent the fuzzy rules. These filters have proven capable to provide excellent robustness in filtering images outside the training set. However, the weighting coefficients can vary as a result of the choice of reference image; in other words, the generalization capability is poor.

On the other hand, the concept of partition-based filtering has been studied and applied to reduce Gaussian noise [2]. Based on the partition concept, an extension to the neural-fuzzy median filter, named the partition fuzzy median (PFM) filter, has been developed [23]. This filter is obtained as the weighted sum of the current pixel value and the output of the median filter. In such an adaptive scheme, the optimal weights of the mutually exclusive blocks are obtained by training over a reference image. To achieve a good balance between noise suppression and detail

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0920-5489/$ – see front matter.
http://dx.doi.org/10.1016/j.csi.2013.09.002

preservation, Lin proposed an adaptive center weighted median (ACWM) filter using the partition concept [20]. Though the weights are derived from the reference image and a relatively large number of partition parameters, both PFM and ACWM filters have shown good efficiency in suppressing noise.

In this paper, a novel partition-based fuzzy median (PBFM) filter with the adaptive resonance theory (ART) applied is to be proposed to fix the drawbacks of the above hard switching schemes and adaptive median filters with trial-and-error parameters. According to fuzzy rules, the PBFM filter partitions the observation vector space using a neural network model based on the adaptive resonance theory (NNM-ART) and thus is able to provide standards for the use of a fuzzy-based median filter that does image restoration. The proposed fuzzy filter is obtained as a weighted sum of the current pixel value and the output of the median filter. The weight of each block is optimized only for the data that fall within that block. This is done by training the filter over a reference image with the least mean square (LMS) algorithm [14]. Such a design of the proposed fuzzy filter helps a lot in simplifying the setup of fuzzy-based median filters as well as the arrangement of the software components concerned. To keep the mean square error down to the minimum, the noise filtering operation is progressively applied through several iterations. Experiment results have demonstrated that the proposed filter significantly outperforms many well-accepted median-based filters. Moreover, the proposed filter also does a great job in removing Gaussian noise as well as mixed Gaussian and impulsive noise.

The rest of this paper is organized as follows. In Section 2, the basic principles of the PBFM filter are introduced. Then, the design of the proposed PBFM filter is detailed in Section 3. In Section 4, the results of some experiments are given to demonstrate the performance of the proposed scheme. Finally, the conclusions are given in Section 5.

2. Principles of adaptive median filter based on fuzzy rules

Let $C = \{k = (k_1,k_2)|1 \le k_1 \le H, 1 \le k_2 \le W\}$ denote the pixel coordinates of a two-dimensional image, where H and W are the image height and width, respectively. A noisy signal at location $k \in C$ is then denoted as $x(k)$. A sample observed, or filter window $w\{k\}$, is defined in terms of the image coordinates symmetrically surrounding the current pixel $x(k)$. The size of the filter window $K = 2n + 1$, where n is a non-negative integer, can be given by:

$$w\{k\} = \left\{x_f(k) : f = 1,\ 2,\ \cdots,\ n,\ n+1,\ \cdots,\ K\right\}, \tag{1}$$

where the input pixel $x(k) = x_{n+1}(k)$ is the central pixel. For example, Fig. 1 shows a 3 × 3 filter window (i.e., $K = 9$) whose center is at pixel $x_5(k)$. This filter window is used throughout this work. The filter window slides across the image pixels in a raster scanning fashion from left to right and from top to bottom.

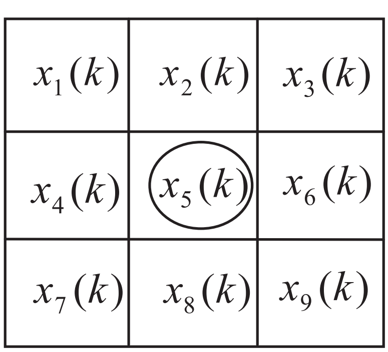

Fig. 1. A 3 × 3 filter window with $x(k) = x_5(k)$.

A schematic diagram of the proposed adaptive median filter based on fuzzy rules is shown in Fig. 2. It is composed of three parts: a median filter, fuzzy rules, and a membership function to help set the degree of noise suppression and image-detail preservation the filter is to perform. The output value $y(k)$ of the adaptive median filter at pixel $x(k)$ can be obtained as follows:

$$y(k) = m(k) + \alpha(k)(x(k) - m(k)), \tag{2}$$

where $m(k)$ denotes the output of the median filter and $\alpha(k)$ denotes the membership function indicating to what extent $x(k)$ is not considered an impulsive noise [1,23]. Each linear combination of the current pixel value and the output of the median filter is taken as an estimate and used for image restoration. If $\alpha(k) = 0$, an impulsive noise is considered to be located at pixel $x(k)$, and the output is then the median value $m(k)$ If $\alpha(k) = 1$, however, then no impulsive noise is considered to exist at $x(k)$, and the output value is the same as that of the original pixel, namely $x(k)$ If $\alpha(k)$ can only be either 0 or 1, the filter functions as a switching median filter; that is, it is a decision-based filter. However, it is oftentimes difficult to make a clear-cut judgment as to whether or not impulsive noise exists at pixel $x(k)$ Therefore, $\alpha(k)$ should take a continuum from 0 to 1 according to fuzzy rules. In other words, deciding the value of the membership function $\alpha(k)$ is the major issue of the proposed PBFM filter.

3. Design of PBFM filter

3.1. Production of fuzzy rules

The membership function $\alpha(k)$ can be set according to the local characteristics of the input signals. In general, the amplitude of most impulsive noise is much more prominent than the fine differences of adjacent signals. Thus, the following three linguistic variables can be defined to generate fuzzy rules.

Definition 1. The value $a(k)$ denotes the absolute difference between input $x(k)$ and median value $m(k)$ as follows [20,23]:

$$a(k) = |x(k) - m(k)|. \tag{3}$$

According to Definition 1, the following fuzzy rule presented in the if-then-else format can be used to judge whether impulsive noise exists.

Rule A: If $a(k)$ is SMALL, then no impulsive noise is assumed present; else an impulsive noise is assumed present [1,20,23].

Rule A implies that a large $a(k)$ value indicates that the input $x(k)$ is corrupted by impulsive noise; that is, $x(k)$ is dissimilar to the median value of filter window $w\{k\}$. Thus, the linguistic variable $a(k)$ is a measure for detecting the possibility of a contaminated input $x(k)$. However, there can be misjudgments if Rule A is the only criterion used to judge whether impulsive noise exists. For example, suppose $x(k)$ is located on a line component with no impulsive noise in the filter window $w\{k\}$. In this case, with only Rule A applied, pixel $x(k)$will be mistakenly

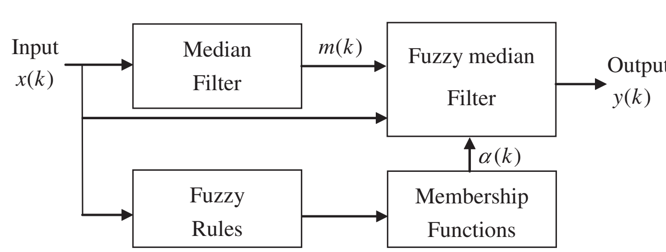

Fig. 2. Schematic diagram of the proposed adaptive median filter.