J. Vis. Commun. Image R. 25 (2014) 478–486

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

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

An effective 2-stage method for removing impulse noise in images

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ARTICLE INFO

Article history:
Received 11 April 2012
Accepted 19 December 2013
Available online 31 December 2013

Keywords:
Impulse noise removal
Weighted mean filter
Robust estimation
Geman-McClure function
Impulse noise detector
Neuro-fuzzy
Image denoising
Adaptive filter

ABSTRACT

In this paper, a robust 2-stage impulse noise removal system is proposed to remove impulse noise from extremely corrupted images. The contributions are in two-fold. First, a neuro-fuzzy based impulse noise detector (NFIDET) is introduced to identify the noisy pixels. NFIDET is a powerful noise detector that can handle image corruption even up to 90% with zero miss and false detection rate with a simple neuro-fuzzy structure. This is the best result among the other impulse noise detectors in the literature. Second, this paper presents a new approach for weight calculation of adaptive weighted mean filter by using robust statistical model. An adaptive robust weighted mean (ARWM) filter removes a detected noisy pixel by adaptively determining filtering window size and replacing a noisy pixel with the weighted mean of the noise-free pixels in its window. A Geman–McClure robust estimation function is used to estimate the weights of the pixels. Simulation results also show that the proposed robust filter substantially outperforms many other existing algorithms in terms of image restoration.

1. Introduction

Digital images are often corrupted by impulse noise during image acquisition or in the transmission channels [1–3]. An important characteristic of this type of noise is that only part of the pixels are corrupted and the rest are noise free.

Various algorithms are known to remove impulse noise while preserving image details. Among them the median filter is widely used because of its outstanding noise suppression ability and high computational efficiency [2]. The weighted median filter [4] and the center weighted median filter [5] were proposed to improve median filter by giving more weight to some selected pixels in the filtering window [6]. However, most of these filters are implemented uniformly across the image and thus remove desirable details in the image and can blur it too.

As a solution to this problem, the switching median-based filters (SMF) [7–18] were introduced, where impulse noise detection algorithms are employed before filtering and the detection results in the filtering process. Only noisy pixels are replaced without touching uncorrupted pixels. The opening-closing sequence (OCS) filter [7], ranked-order based adaptive median (RAM) filter [8], progressive switching median (PSM) filter [9], Laplacian detector-based switching median (LDSM) filter [10], pixel-wise MAD-based (PWMAD) filter [11], median-type noise detectors and detail-preserving regularization [DPR] filter [33] and adaptive median and improved edge-preserving regularization AM-IEPR[34] filter are examples of this type of filters.

In the switching median filter, the performance of the impulse noise detector is crucial, because the whole filtering procedure is affected by the result. However, most of the algorithms given above perform badly in noise detection and damage important image details or retain numerous impulses in the filtered images at a high noise ratio.

Another SMF, the noise adaptive soft switching median (NASM) filter was proposed in [12]. The NASM achieves a highly good performance in removing impulse noise and preserving signal details. However, for high noise ratio the performance of the filter is reduced significantly due to an increased number of misclassified pixels. In [13] the boundary discriminative noise detection (BDND) algorithm was proposed. In this method, decision boundaries are determined to classify pixels as “corrupted” or “uncorrupted”; however, the misclassified rate is not very good. In switching based adaptive weighted mean (SAWM) algorithm [14], the reliability of the decision boundaries in BDND is enhanced and the misclassification rate is highly reduced. In [15], another algorithm was proposed which modifies the BDND algorithm and obtains zero misclassification rates with a low false detection rate.

In [19], a neuro-fuzzy (NF) based impulse noise detector was proposed. This detector consists of two identical NF sub-detectors and a decision maker. Its algorithm requires a long computation and execution time since it includes two 3- input NF detectors and a decision maker. However, for the corrupted images with noise greater than 50% the performance of the detector is significantly reduced.

In this paper, we propose a two stage high performance noise removal system with a neuro-fuzzy (NF) impulse noise detector and adaptive robust weighted mean (ARWM) filter. A neuro-fuzzy

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http://dx.doi.org/10.1016/j.jvcir.2013.12.016

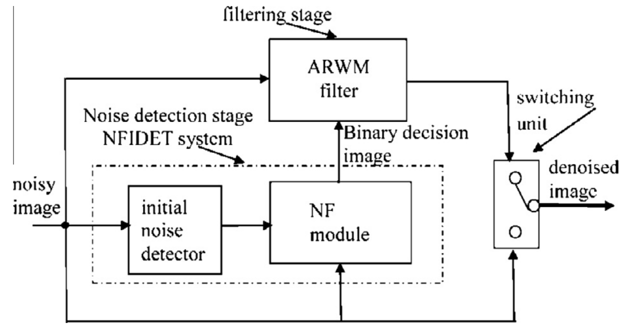

Fig. 1. Noise removal system.

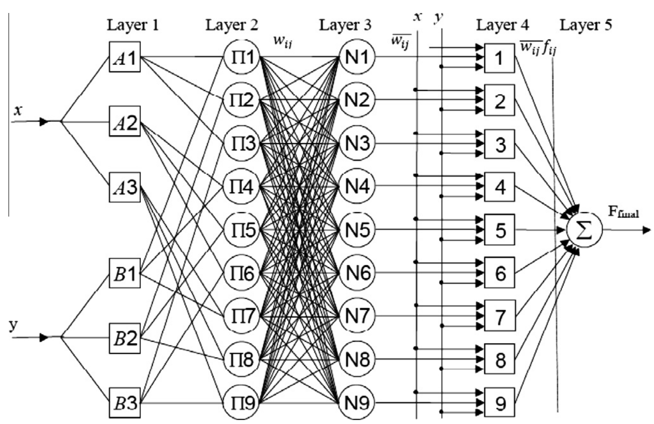

Fig. 2. ANFIS structure used in proposed NFIDET.

based impulse noise detector (NFIDET) is based on NF techniques and it can handle image corruption even up to 90% noise with zero miss and false detection rate with a simple NF structure. In the filtering process we applied the ARWM filter to remove impulse noise. The Geman–McClure robust estimation is used to estimate the weights of these pixels. Here the denoised output pixel is the weighted average of noise-free pixels with the surrounding neighborhoods using the chosen robust estimation function. Since the noise detection plays the key role on filtering process, our filter has superior performance in terms of the subjective quality of the filtered image as well as the objective quality in the peak signal-to-noise ratio (PSNR) measurement respect to that of other filters.

2. Noise removal system architecture

The noise removal system (Fig. 1) consists of two stages: noise detection and filtering. Noise detection is critical for the performance of the noise removal algorithm. In our system NFIDET is designed to detect impulse noise with very high detection rate and the ARWM filter is then used to filter detected noisy pixels.

2.1. Noise model

The noise is modeled as the salt-and-pepper impulse noise. Pixels are randomly corrupted by two fixed extreme values, 0 and 255 (for 8-bit monochrome image), generated with the same probability.

Let $o_{(i,j)}$ and $f_{(i,j)}$ denote the intensity values of the original image and the observed noisy image at pixel location (i, j) with the same size respectively,

$$f_{(i,j)} = \begin{cases} n_{(i,j)} & \text{with probability } p \\ o_{(i,j)} & \text{with probability } (1-p) \end{cases} \tag{1}$$

where $n_{(i,j)}$ is the gray-level value of the noisy pixel. When the images are contaminated by the impulse noise of fixed value the noisy pixels are equal to 0 or 255 each with equal probability $p/2$. Here, p denotes the noise ratio $(0 < p < 1)$.

2.2. Structure of the neuro-fuzzy based impulse noise detector (NFIDET)

The NFIDET consists of an initial Noise Detector and a NF module. NFIDET algorithm starts with the input of the noisy image to the initial noise detector. The output of the initial noise detector together with the noisy image itself is the input to the NF module. The target of the NF module generates a binary image called the binary decision image whose pixel value is 1 for an impulse pixel and 0 for other pixels. The ARWM filter then utilizes this image file for noise removal. Only the values of the corrupted pixels are changed and the rest remain the same during the filtering process.

(1) *Initial noise detector*: The initial impulse noise detector uses local image statistics proposed in [20] to identify noisy pixels.

Consider $(2W + 1) \times (2W + 1)$ window symmetrically surrounds the test pixel $f_{(i,j)}$, defined by

$$\{f_{(i+s,j+t)} \quad -W \leqslant s,t \leqslant W\}$$

The absolute value of the difference between the gray level values of $f_{(i,j)}$ and other neighbor pixels in the window are calculated as

$$Dif_{(s,t)} = |f_{(i,j)} - f_{(i+s,j+t)}| \tag{2}$$

Then, the sorted *Dif* values in the increasing order are applied to obtain r_i values and to define

$$SDif = \sum_{i=1}^{n} r_i \tag{3}$$

The *SDif* value is used to detect the noisy pixel. If this value is greater than a certain threshold T, then it is considered as the noisy pixel. Otherwise the pixel is considered as noise free. The selection of the threshold T and n are done experimentally. For the large variety of images we tested, excellent results were obtained using threshold T selected from the interval 96–104 and n as a 4.

In [20] it was suggested to use the 5×5 windows ($W = 2$) and $n = 12$ if the noise ratio is higher than 25%, and to use the 3×3 windows ($W = 1$) and $n = 4$ otherwise. In contrast to [20], we used 3×3 window ($W = 1$) and $n = 4$ for all noise densities (20–90%). Since, this is the initial noise detector and the output of the initial detector will be re-evaluated in NF network.

(2) *The NF module*: The NF module generates a binary decision image. In this study an adaptive neuro-fuzzy inference system (ANFIS) is used for NF network. ANFIS is a well-known neuro-fuzzy system and uses a first order *Takagi–Sugeno–Kang* (TSK) [21,22] type fuzzy system. The ANFIS used in proposed module has two inputs (x, y) and one output (F_{final}). One of the inputs (x), of the NF module is fed with noisy image while the other input (y) is fed with the initial noise detector output image, and output is the

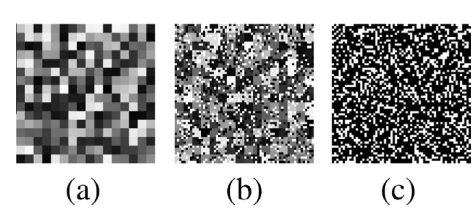

Fig. 3. (a) Original 64 × 64 image (b) training image (c) target image.