



Using decision tree, particle swarm optimization, and support vector regression to design a median-type filter with a 2-level impulse detector for image enhancement

Hung-Hsu Tsai^a, Bae-Muu Chang^{b,*}, Xuan-Ping Lin^a

^a Department of Information Management, National Formosa University, Hu-Wei, Yun-Lin 632, Taiwan, ROC

^b Department of Information Management, Chienkuo Technology University, Chang-Hua, Chang-Hua 500, Taiwan, ROC

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ABSTRACT

The paper presents a system using Decision tree, Particle swarm optimization, and Support vector regression to design a Median-type filter with a 2-level impulse detector for image enhancement, called DPSM filter. First, it employs a varying 2-level hybrid impulse noise detector (IND) to determine whether a pixel is contaminated by impulse noises or not. The 2-level IND is constructed by a decision tree (DT) which is built via combining 10 impulse noise detectors. Also, the particle swarm optimization (PSO) algorithm is exploited to optimize the DT. Subsequently, the DPSM filter utilizes the median-type filter with the support vector regression (MTSVR) to restore the corrupted pixels. Experimental results demonstrate that the DPSM filter achieves high performance for detecting and restoring impulse noises, and also outperforms the existing well-known methods under consideration in the paper.

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1. Introduction

Digital images may be disturbed or damaged by impulse noises due to their transmission through an unreliable channel [15]. The existence of noises in the digital images severely results in image distortion and then several image processing systems cannot achieve the desired results, such as image segmentation, edge detection, and object recognition. Hence, prior to the development of image processing systems, the image noise filtering is an extremely necessary pre-processing procedure for these systems [1–3,7–14,16,17,19,22,24,25].

In recent years, several various filtering algorithms have been proposed for impulse noise removal in the grey-level images [1–3,7–14,16,17,19,22,24,25]. The median filter which is nonlinear is widely employed and effectively removes impulse noises [7,8,12,22,25]. It replaces the central pixel of a filter window with the median among all pixels in the window. However, it cannot sufficiently classify the input pixels as either noise-corrupted or noise-free when these pixels are on the thin lines or edges. Later, various modified median-based filters, such as the center weighted median (CWM) filter and the fuzzy-rule-based median (FM) filter, have been presented to improve the disadvantages of typical median filters which still blur some details and often damage the edges [16].

In order to overcome the drawback of median filters, the decision-based filters with an IND, as shown in Fig. 1, have been proposed [1–3,6–8,17–19,24]. The IND is employed to determine whether the pixels of an input image are corrupted or not. In [24], the switching median (SM) filter determines whether the central pixel of filter window is corrupted or not, according

* Corresponding author. Tel.: +886 9 377 49299; fax: +886 4 711 1142.

E-mail addresses: thh@nfu.edu.tw (H.-H. Tsai), bmchang@cc.ctu.edu.tw (B.-M. Chang), no300601@gmail.com (X.-P. Lin).

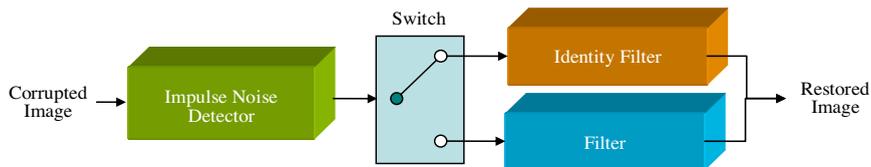


Fig. 1. The decision-based filter with an impulse noise detector (IND).

to the difference between the central pixel and the median among all pixels in the filter window. If the difference is larger than the predefined threshold, the central pixel is considered as noise-corrupted and then it is replaced by the median of filter window. Otherwise, it is kept unchanged [24].

The above filters require the thresholds to classify the central pixel of filter window as either noise-corrupted or noise-free [3,17,24]. These thresholds, which severely affect the performance for the noise-detection, are manually determined in a trial-and-error fashion. In one of our previous works, a decision-based image filter was proposed. It contains a hybrid IND realized by a DT which is built via integrating the features of 10 impulse noise-detection algorithms. Furthermore, the PSO algorithm well determines a set of approximately optimal combinations of 10 impulse noise detectors and a set of nearly optimal parameters for the thresholds in the DT [5]. Although the proposed filter can effectively detect the corrupted pixels in an image, it often raises misclassifications for impulse noise-detection in the case of high corruption rates. The situation leads to the poor filtering performance of our proposed filter [5]. This motivates us to develop the DPSM filter. It employs a 2-level IND with varying filter windows to promote the detection rate for the IND. Moreover, it adopts the support vector regression (SVR) and the filter windows with varying sizes to improve the filtering performance.

In this paper, the DPSM method belongs to the category of decision-based filters. The purpose for the noise-detection is detecting the central pixel of filter window whether it is corrupted or not. Hence, the noise-detection can be strongly regarded as a classification problem. The thresholds for classifications are definitely required. While building a DT to be the 2-level IND, the combinations for these thresholds among 10 detectors are very enormous. It is an NP-hard problem to search for the acceptable combination for 10 detectors and their corresponding calculations for the thresholds. Thus, the PSO algorithm is then utilized to find out an approximate solution. That is, it is essential to employ a systematic approach for finding out the appropriate thresholds and the optimized combinations. Here, the 2-level hybrid IND can reduce the misclassifications for the noise-detection. As a result, the SVR is employed to devise the MTSVR filter to improve the performance of progressive noise-free ordered median (PNOM) filter in the MDP system [5]. The main contribution of this paper is to design a decision-based filter with the noise-detection, developed by using the DT to overcome the misclassifications in the noise-detection, which is one of machine learning approaches.

This paper integrates computational intelligence methods, the PSO algorithm and the SVR, with a machine learning scheme, DT, to improve the image-restoration of existing filters under consideration. The 2-level IND can promote the accuracy rates of noise detectors, which is realized by the DT via integrating 10 impulse noise detectors. Additionally, the SVR possesses generalization capability that can enhance the performance of MTSVR filter. Again, the significant contribution of this paper is to integrate the computational intelligence with the machine learning to develop a novel kind of image filters. Therefore, our researches are progressive from image representation to machine learning.

The remainder of this work is arranged as follows. Section 2 states basic principles for the DT, the PSO, and the SVR. In Section 3, the design for the DPSM filter is described. The training diagrams for the proposed 2-level IND and the MTSVR filter are also described in this section. In Section 4, the experimental results show the comparisons for the PSNR values and the restored images at various noise ratios in some corrupted images for different well-known filters. Finally, conclusions are drawn in Section 5.

2. Basic principles

2.1. The representation for the grey-level images

A grey-level image is represented as a two-dimensional $L \times K$ matrix $X = \{x_{ij} | 1 \leq i \leq L, 1 \leq j \leq K\}$, where L and K are its height and width, respectively, and $x_{ij} \in \{0, 1, 2, \dots, 255\}$ is the pixel grey-level value at position (i, j) in X . A filter window with size $S = (2\tau + 1)^2 = 2n + 1$ slides over the image X at position (i, j) to formulate a sample matrix X_{ij} , where $1 \leq i \leq L$, $1 \leq j \leq K$, and S is generally an odd number. Let the value for the central pixel in the filter window X_{ij} be x_{ij} . The filter window X_{ij} usually slides over the image X from left to right and top to bottom. For better clarity, the sample matrix X_{ij} can be rewritten as a one-dimensional vector $\mathbf{x}(k)$ represented by

$$\mathbf{x}(k) = (x_{-n}(k), \dots, x_{-1}(k), x_0(k), x_1(k), \dots, x_n(k)), \quad (1)$$

where $x_0(k)$ (or $x(k)$) is the original central pixel value at location k , $k = (i - 1) \times K + j$ indicates the pixel located at position (i, j) in the image X , and $x_0(k)$ (or $x(k)$) stands for the central pixel in the filter window. For clarity, $x(k)$ and $x_0(k)$ are used interchangeably throughout this paper. Also, the filter window X_{ij} and its corresponding one-dimensional vector $\mathbf{x}(k)$ are employed alternatively [5].

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