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Multi-level adaptive switching filters for highly corrupted images ☆

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ABSTRACT

The performance of a switching filter is highly dependent on its detection accuracy. Inspired by adaptive median filter methodology, this paper proposes a multi-level adaptive switching filter (MASF) for the recovery of highly corrupted images. In particular, the adaptive technique is employed in all the detective, edge-preserving and restorative stages in order to improve noise discrimination and suppression simultaneously. Most critical design parameters in the proposed algorithm, e.g., the limit of window-expansion size and the noise range, are self-adaptive so as to retain simple implementation and high computational efficiency. Furthermore, several effective modifications on both stages of the MASF, such as the convergence factor, switching initialization and spatial adaptive weighting, are also introduced in order to provide better and more robust results. Monte-Carlo simulations show that the MASF outperforms many existing state-of-the-art algorithms in terms of both visual and quantitative results.

1. Introduction

Images are frequently corrupted by fixed-valued impulse noises, which is the result of errors generated in sensors and communication channels during image acquisition and transmission. It is thus essential that impulse noises be reduced or removed in order to ensure good performance in subsequent image processes, such as edge detection, segmentation and compression. The most widely used approach for suppressing impulse noise is to use median-based filters (MF) [1], however MF only provides good outputs at low noise level percentages, and struggles with higher levels of noise. Various modified filtering algorithms have been proposed for the removal of high-density impulse noise. Some sophisticated examples include: weighted median filtering, center weighted median filter [2], recursive median filters [3] and adaptive median filter (AMF) [4]. Of these, AMF has a variable window size, and is widely used because it effectively suppresses noise and exhibits simpler principles [5]. However, since the classical filters identically modify both noise and noise-free pixels, some desirable details may be blurred. As a solution to this problem, the switching techniques [6–8] have also been introduced. These filters detect whether a given pixel is corrupted, and then restore only that corrupted pixel. Combining these two features, the adaptive switching median filter (ASMF) had been the subject of a number of studies in recent years [9–12].

The boundary discriminative noise detection (BDND) algorithm [10] is a successful paradigm of ASMF, and offers better performance compared with many other filters. One of the main contributions in [10] is to propose four generalized models of salt and pepper (S&P) noise. In order to well discriminate these new noises, BDND examines a pixel from coarse (21×21 window) to fine (3×3 window). It only classifies the central pixel as "corrupted" if both examinations yield the same result, and then uses a noise-adaptive median filter to restore the corrupted pixels. Obviously, the performance of a switching scheme is highly dependent on its detection accuracy. In an effective BDND (EBDND) algorithm [13], the reliability of the decision boundaries in BDND is enhanced and obtains zero misclassification rates. In [14], advanced BDND algorithm (ABDND) was proposed, which modifies the BDND algorithm, and the false detection rate was highly reduced. However, these modified methods require either prior knowledge or a histogram analysis to obtain the noise range. This makes ABDND and EBDND unsuitable for real-time application. Recently, Jafar et al. [15] (IBDND) also proposed two modifications to the BDND filter for removing high-density impulse noises. However, there has been no study on detection performance.

Furthermore, it can be observed that there are two more obvious drawbacks to the BDND. First, the processing time is rather high since it uses a very large window size (21×21) in "all" pixels

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255	52	210
52	210	0
210	210	210

(a)

60	62	62
61	60	62
255	63	63

(b)

Fig. 1. Two hypothetical noisy sub-images.

regardless of their noisy conditions. Second, the BDND derives the decision boundaries corresponding to the maximum differences in the left and right half intervals. Thus, false detection easily occurs in windows that contain a strong edge, such that the maximum difference is occasionally obtained in pixels at different sides of the edge. Inspired by the intuitive and simple nature of AMF, this paper proposes a novel and efficient multi-level adaptive switching filter (named MASF) to cope with the above problems. To a certain extent, the proposed algorithm acts an inverse inference of the classical BDND method. However, the MASF is designed to conquer the constraints in high-level noise filtering, impulse noise suppression and detail preservation, in a highly corrupted image without compromising the computational efficiency. In particular, the adaptive technique is first employed in the detection stage to improve high-density noise discrimination. Instead of working with a 21×21 window in every pixel, the MASF examines each pixel from fine to coarse. It first checks whether the smallest window contains enough information to classify the noisy condition of

Algorithm 1 (Adaptive BDND Detector):

For each pixel location (i, j), do the following.

Step 1) Initialize $k = 1$.
Step 2) Get the window size $W = 2k + 1$, if W reaches the maximum limit then go to Step 9, else impose a $W \times W$ window centres on $x_{i,j}$.
Step 3) Sort the pixels lie in the window region to an ordered vector V_O.
Step 4) Compute the difference vector D_V of V_O.
Step 5) Find the pixels v_L and v_R which correspond to the most left and right significant differences d_L and d_R in D_V. The significant difference is defined as (2).
Step 6) If D_s is empty, calculate $\hat{m} = \sum D_V$, $v_L = V_o(W^2)$, $v_R = V_o(1)$.
elseif $No(D_s) = 1$, $\hat{m} = \sum D_V - d_R$
else $\hat{m}$ is obtained from (3).
Step 7) Update the two decision boundaries as (4)
Step 8) If the amount of pixels between b_L and b_R is less than $\frac{1}{3k}(w \times w)$, increases $k = k + 1$ and go to Step 2.
Step 9) Classify the pixels $x_{i,j}$ into three clusters according to (1). If $x_{i,j}$ is an S&P noise, register the same location (i, j) in the noise map P_N as 0 and the size map P_S as k.

Fig. 2. The detective stage of the MASF algorithm.

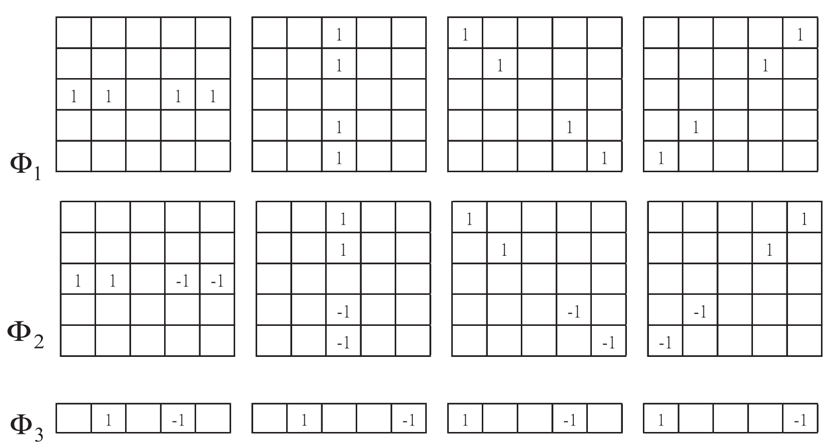

Fig. 3. Three sets of four 5×5 convolution kernels.

20	20	23	22	21
22	21	18	19	152
21	22	20	151	152
21	20	152	150	153
22	150	151	149	153

(a)

*	20	23	*	*
22	*	*	*	152
21	*	*	*	152
21	*	*	*	153
*	*	*	149	153

(b)

	20	*	*	21
22	*	*	*	152
21	*	*	*	152
*	*	*	*	153
22	*	*	149	153

(c)

Fig. 4. The illustrated examples given in [15], (a) hypothetical image, (b) noised image and (c) another possible noised image.