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Probabilistic decision based filter to remove impulse noise using patch else trimmed median

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ABSTRACT

A new probabilistic decision based filter (PDBF) is presented to remove salt and pepper impulse noise in highly corrupted images. The filter employs two types of estimation techniques for denoising namely trimmed median (TM) and patch else trimmed median (PETM) which is our main contribution in this paper. Depending upon the estimated noise density, the filter utilizes either TM or PETM and hence enhanced outcome of denoising. Simulation results prove that the PDBF has outperformed recently proposed state-of-the-art filters in terms of peak signal to noise ratio (PSNR), structural similarity index (SSIM), image enhancement factor (IEF), mean absolute error (MAE) and visual representation at the noise densities (ND) as high as 95%.

1. Introduction

Digital images are often contaminated by salt and pepper noise during the process of acquisition and transmission. Numerous algorithms have been proposed to restore the images from this impulse noise and median filtering is the basic core in their developments. Standard median filter (SMF) [1] is a simple nonlinear filter developed to remove salt and pepper noise in an effective manner. As the SMF alters each pixel of an image by a median of samples available in the given window, it fails to preserve high frequency components present in the image and hence poor denoising results especially at medium and high noise densities (ND > 30%). To improve the denoising results, variations in median filtering [2–20] have been proposed by incorporating the important concepts called *weighted median*, *adaptive median*, *switching median*, *trimmed median* and a controlled mixture of these key concepts: *weighted median* – multiplying the predefined weights to selected pixels in the given window before finding the median, *adaptive median* – altering the size of the window in order to get a noise free estimate, *switching median* – replacing the noisy pixels by the respective median values while keeping noise free pixels unaltered, *trimmed median* – finding median among noise free pixels only. Among these filters [2–20], we consider six distinguished state-of-the-art filters, namely, a decision based algorithm (DBA) [9], simple adaptive median filtering (SAMF) [10], noise adaptive fuzzy switching median filter (NAFSM) [15], modified decision based un-symmetric trimmed median filter (MDBUTMF) [17], new algorithms for removing impulse noise (NARIN) [18], adaptive weighted mean filter (AWMF) [19], fast switching based median–mean filter (FSMMF) [20], for their unique identity and competence. The DBA [9] employs switching median concept in which each noisy pixel is replaced either by the sample estimated by a fast and unique procedure employing 3×3 window centered around noisy pixel or by the just past processed sample. Though the DBA performs well at low and medium noise densities (ND < 50%) it gives out undesirable streaking effect in the denoised images at high noise densities (ND > 60%). The SAMF [10] is basically an adaptive-switching-trimmed-median filter which replaces each noisy sample by the estimation obtained from only the noise free samples available in adaptive windows. Though the SAMF delivers good denoising results in terms of PSNR and SSIM, it fails to restore the high frequency information available in the images at high noise densities. Moreover, execution time of SAMF is large and increases in accordance with the amount of noise density. The NAFSM [15] is an adaptive-fuzzy based-switching-median filter which gives a very good visual representation but only for low and

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medium noise densities. MDBUTMF [17] is a fast switching/decision based trimmed-median filter which is basically a simplified version of SAMF and gives very good denoising results in terms of PSNR and SSIM at low and medium noise densities. A fixed 3×3 window employed in MDBUTMF fails to give a good estimation for noisy pixels at high noise densities and hence poor denoising results. The NARIN [18] is a derivative of adaptive median filtering (AMF) [6], which employs an orderly and repeated application of AMF and hence improved denoising performance over AMF. Similarly, AWMF [19] is a latest good performing filter which is basically an extended version of AMF, where the mean filtering is employed instead of median filtering. Though the AWMF delivers good denoising performance it requires extremely large execution time at all the noise densities. Recently proposed FSMMF [20] is a fixed window-switching-median filter which also employs a causal mean filter to give better denoising results at a faster rate. The proposed probabilistic decision based filter (PDBF) employs a new estimation technique called patch else trimmed median (PETM) using which it excellently outperforms the recently developed standard and state-of-the-art algorithms.

The rest of the paper is organized as follows. Section 2 demonstrates the development of new estimation procedure PETM and Section 3 presents the algorithm of PDBF. Section 4 gives the experimental results and finally the conclusion is drawn in Section 5.

2. Patch else trimmed median

As a part of development to derive our PDBF algorithm, let us introduce a new estimation called patch median which is defined as follows: patch median (PM) of given square patch (matrix) of an odd size is defined as the pixel value at the center of the diagonal of matrix, after arranging the patch element values in rows/columns and then columns/rows either ascending or descending. The PM always gives a single sample output, unlike the trimmed median

$$\begin{array}{|c|c|c|} \hline 255 & 255 & 147 \\ \hline 134 & 0 & 255 \\ \hline 0 & 141 & 145 \\ \hline \end{array} \quad \underset{\text{Row ordering}}{\begin{array}{|c|c|c|} \hline 147 & 255 & 255 \\ \hline 0 & 134 & 255 \\ \hline 0 & 141 & 145 \\ \hline \end{array}} \quad \underset{\text{Column ordering}}{\begin{array}{|c|c|c|} \hline 0 & 134 & 145 \\ \hline 0 & \mathbf{141} & 255 \\ \hline 147 & 255 & 255 \\ \hline \end{array}}$$

Patch median = 141
Trimmed Median = Median of [134,141,145,147] = (141+145) / 2 = 143

Fig. 1. An illustration for patch median and trimmed median.

(TM) [17] where there is a possibility of averaged output as illustrated in Fig. 1.

The filter employing PM can be termed as a patch median filter (PMF) which is always outperforming SMF in terms of PSNR and visual appearance. We have conducted several experiments to compare PMF versus SMF and we present a simple experimental result in Fig. 2 as an example. Fig. 2(a) illustrates that the PMF gives an improvement over SMF in terms of PSNR and it has been clearly presented using 10 different noisy images corrupted with noise density ND(%) = [20, 40, 60, 80]. Fig. 2(b) shows the improvement in visual appearance given by PMF against SMF for noisy *Lena.png* and *House.png* image corrupted at ND = 60%. Consequently Fig. 2 clearly demonstrates that the PMF gives a definite improvement in PSNR and visual appearance over that of SMF for the same size of working window.

It has already been established that the trimmed median filters TMF [10,17] employing TM gives the best denoising performance at low and medium noise densities as there exist enough number of samples for estimation. But if noise density increases, the number of noise free samples (*nfs*) available in the given window is getting minimum and the probability of getting an even number of *nfs* increases, which leads to poor estimation. For example, if ND = 70%, the probable number of noisy samples available in a 3×3 window is 7 ($0.7 \times 9 = 6.3 \approx 7$) and hence the number of *nfs* is 2. If suppose those *nfs* samples are not adjacent to each other in the given 3×3 window, averaging of such samples (need to be found for trimmed

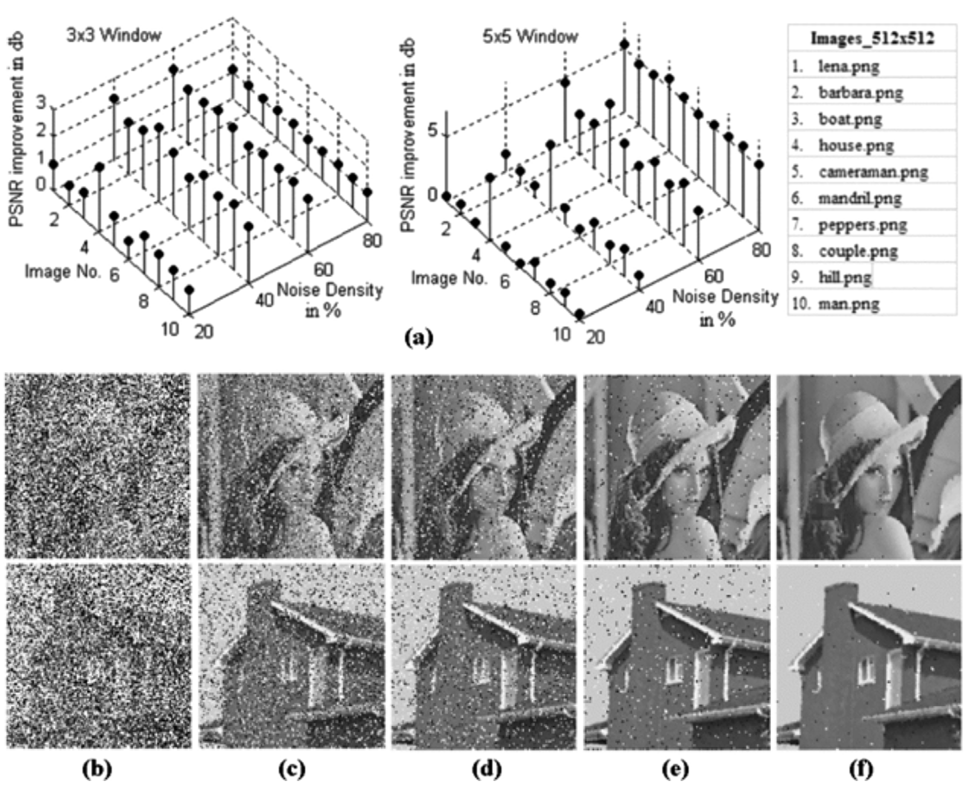

Fig. 2. (a) Incremental improvement in PSNR given by PMF over SMF for 10 different noisy images corrupted with the noise density, ND (%) = [20, 40, 60, 80]; (b) noisy *Lena.png* and *House.png* images (ND = 60%), denoising results obtained using: (c) SMF (3×3); (d) PMF (3×3); (e) SMF (5×5); and (f) PMF (5×5).