Salt-and-Pepper Noise Detection and Reduction Using Fuzzy Switching Median Filter

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**Abstract — ***This paper presents a new fuzzy switching median (FSM) filter employing fuzzy techniques in image processing. The proposed filter is able to remove salt-and-pepper noise in digital images while preserving image details and textures very well. By incorporating fuzzy reasoning in correcting the detected noisy pixel, the low complexity FSM filter is able to outperform some well known existing salt-and-pepper noise fuzzy and classical filters*[1].

Index Terms — Fuzzy switching median, salt-and-pepper noise, image processing, fuzzy reasoning.

I. INTRODUCTION

Digital images acquired through many consumer electronics products are often corrupted by salt-and-pepper noise during image acquisition, recording and transmission [1]. The source of contamination originates from household electrical appliances, external disturbance such as atmospheric disturbance, noisy sensor and channel transmission errors. It is important to eliminate salt-and-pepper noise contained in the images and at the same time preserving the image integrity. This is imperative as the processed image will be later used for subsequent image processing operations such as edge detection, image segmentation and others.

Although many methods have appeared in scientific literatures, each has its own advantages and limitations. The performance of a particular salt-and-pepper noise filter normally increases with the complexity of the implemented algorithm. On the other hand, methods with low complexity filter salt-and-pepper noise at the expense of image details and textures. Moreover, some method requires laborious calculations and tuning of parameters used in the filtering algorithm.

Specifically for removal of salt-and-pepper noise, conventional median filters and other classes of modified median filters [2], [3] are widely used. However, median filtering would simply restore the processed pixel even when the pixel is a noise-free pixel. The Laplacian switching-median filter proposed in [2] is able to preserve fine details but could not remove high level of salt-and-pepper noise. Then, the fuzzy inference ruled by else-action (FIRE) filter introduced by Russo [4] suggests that effective removal of salt-and-pepper noise can be achieved by using a fuzzy rulebase and employing fuzzy sets, although the FIRE filter itself still could not properly remove noise present at objects' edge.

Recently, an efficient method in the removal of salt-and-pepper noise is introduced in [1]. With the growing appeal of fuzzy logic, employing fuzzy theories as an extension to the existing classical filters may prove useful and effective in the domain of noise removal in image processing. The filter in [1], for example, incorporates fuzzy set theory and its performance outperforms some algorithms described in existing literatures, such as the works in [2]-[5].

In this paper, modifications to [1] have been proposed to improve the filter performance in salt-and-pepper noise detection and cancellation. This new recursive filter is called the fuzzy switching median (FSM) filter. The FSM filter is composed of two semi-dependent modules, namely the salt-and-pepper noise detection module and the fuzzy noise cancellation module. The fuzzy set used for noise cancellation does not require time-consuming tuning of parameters and thus no training scheme is required. This marked the simplicity of the proposed algorithm.

This paper is organized as follows: Section II briefly describes the definition of salt-and-pepper noise before presenting in detail the salt-and-pepper noise detection module and the fuzzy inference mechanism used in noise cancellation module. Section III analyzes the result obtained for the proposed filter and at the same time comparing it to other existing techniques, and, finally, Section IV concludes the work of this paper.

II. THE FUZZY SWITCHING MEDIAN FILTER

Let us suppose we are dealing with grayscale digital image which intensity is stored in an 8-bit integer, giving a possible 256 gray levels in the interval [0, 255]. In this interval, a salt-and-pepper noise takes on the minimum and maximum intensities and appears in digital image with certain probabilities. The noise can be either positive or negative [6]. Positive impulse appears as white (salt) points with intensity 255 and probability p_w in the image. Conversely, negative impulse appears as black (pepper) points with intensity 0 and

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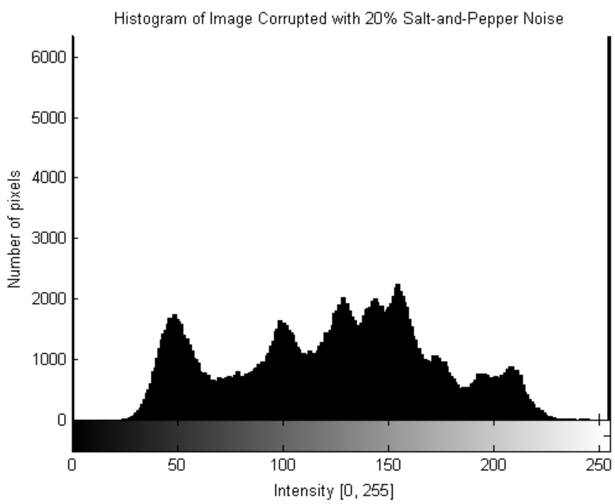
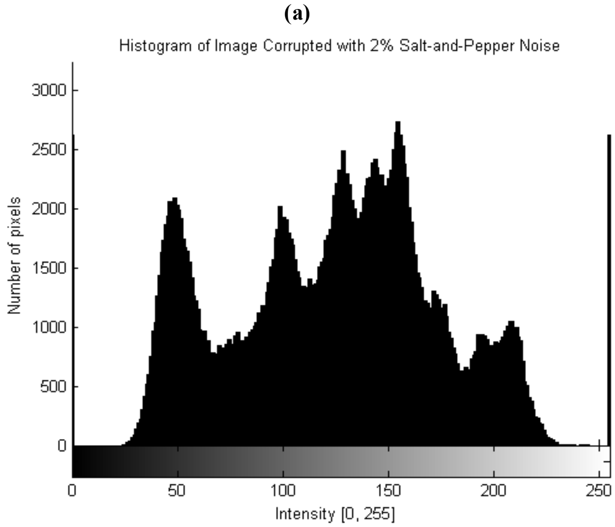
probability p_b in the image. In this paper, we define a low level salt-and-pepper noise as one having probability lies in the range 0 and up to $p = p_w + p_b = 0.25$, where $p_w = p_b$. If $p = 0.45$ or higher, the image is regarded as corrupted by high level of salt-and-pepper noise. Otherwise, the image is said to be corrupted by a moderately high level of salt-and-pepper noise.

A. Salt-and-Pepper Noise Detection Module

The salt-and-pepper noise detection algorithm is based on the fact that a digital image corrupted by salt-and-pepper noise with probability p would produce two peaks at intensities 0 and 255 when evaluating the histogram of the noisy image. Therefore, the detection algorithm would begin by searching in the noisy image for the two intensities of positive and negative noise pulses. Such a detection method has been proposed in [1] based on methods in [3], [4], [7] and [8].



(a)



(b)

Fig. 1. Histogram of grayscale "Lena" image of size 512×512 corrupted with: (a) 20% salt-and-pepper noise, and (b) 2% salt-and-pepper noise.

Fig. 1 (a) and (b) show the histograms for a grayscale test image "Lena" of size 512×512, corrupted with 20% and 2% salt-and-pepper noise, respectively. For the image corrupted by 20% salt-and-pepper noise, the intensities of the noise would peak at the ends of the noisy image histogram. Under this condition, the assumption on salt-and-pepper noise intensities are also the intensities of the peaks of the noisy image histogram is true. However, when the image is corrupted with a low level of salt-and-pepper noise, such as the one shown in Fig. 1 (b), the positive noise peak is lower than intensity belongs to a group of pixels in the image which is noiseless. Thus, if the detection algorithm revolves around the assumption that says the intensities of salt-and-pepper noise are the intensities of peaks in the noisy image histogram, then it is likely the noisy pixels in the image would be left unchanged when the image is corrupted with low level of salt-and-pepper noise.

To avoid the problem of detecting wrong salt-and-pepper noise intensities, the proposed salt-and-pepper noise detection algorithm requires the search for the two noisy peaks is to be conducted in two directions starting from the two ends of the noisy image histogram. Traversing the noisy image histogram from the left-side end toward the center of the histogram, the search is halted once the local maximum is found. The procedure is repeated for the right-side end.

Local maximum is defined as the first peak encountered when traversing in a particular direction. Thus, the intensity of negative noise is known as the lower-end local maximum called L_{lower}, when travelling from the left-side end of the histogram towards the center. Similarly, the positive noise intensity is the upper-end local maximum called L_{upper}, when travelling from the right-side end of the histogram towards the center of the histogram. For a 256 gray levels image, normally $L_{upper} = 255$ and $L_{lower} = 0$; although L_{upper} and L_{lower} can assume some other intensities in general.

Once the two impulsive intensities are found, the filtering action would begin by windowing the noisy image starting from the upper-left corner to the bottom-right corner of the noisy image. Defining the filtering window $W_{i,j}$ of size $(2N+1)\times(2N+1)$ and pixel $x_{i,j}$ centered at position (i, j), $W_{i,j}$ can be written as:

$$W_{i,j} = \{x_{i-N,j-N}, \ldots, x_{i,j}, \ldots, x_{i+N,j+N}\} \quad (1)$$

Since the proposed FSM filter is using a 3×3 filtering window, (1) is reduced to:

$$W_{i,j} = \{x_{i-1,j-1}, \ldots, x_{i,j}, \ldots, x_{i+1,j+1}\} \quad (2)$$

The central pixel $x_{i,j}$ in the 3×3 filtering window is compared with L_{upper} and L_{lower}. If the central pixel $x_{i,j}$ in processing matches one of the two impulsive intensities, then $x_{i,j}$ is more likely to be a noisy pixel. In order to perform a correction on $x_{i,j}$, or to handle an exception when $x_{i,j}$ is noiseless but matches one of the impulsive intensities, the second action module resorting to fuzzy reasoning is executed.

As long as $x_{i,j}$ equals any of the two salt-and-pepper noise intensities, the absolute luminance difference $g_{i+k,j+l}$ between the neighboring pixels and the central pixel in 3×3 window is calculated using (3):

$$g_{i+k,j+l} = | x_{i+k,j+l} - x_{i,j} | \text{ with } k,l \in (-1,0,1) \text{ and } x_{i+k,j+l} \neq x_{i,j} \tag{3}$$

Next, the fuzzy input variable $G_{i,j}$ is determined. In contrast to [1], $G_{i,j}$ is the maximum fuzzy gradient value in the 3×3 filtering window and is given by:

$$G_{i,j} = \max\{g_{i+k,j+l}\} \tag{4}$$

Equation (4) dictates that the maximum value of the absolute gradient among the eight neighboring pixels of $x_{i,j}$ in the 3×3 window $W_{i,j}$ will be used as the fuzzy input variable. The choice of selection on using the maximum operator over minimum operator will be explained in due time.

The fuzzy set (see Fig. 2) processes the neighborhood information represented by the input fuzzy variable $G_{i,j}$ to estimate a correction term which aims at cancelling the noise. Mathematically, the fuzzy set $f_{i,j}$ which is taken from [1], is given by:

$$f_{i,j} = \begin{cases} 0 & : \quad 0 \leq G_{i,j} < T_1 \\ \dfrac{G_{i,j} - T_1}{T_2 - T_1} & : \quad T_1 \leq G_{i,j} < T_2 \\ 1 & : \quad \text{otherwise} \end{cases} \tag{5}$$

where T_1 and T_2 are the thresholds to perform partial correction as shown in Fig. 2.

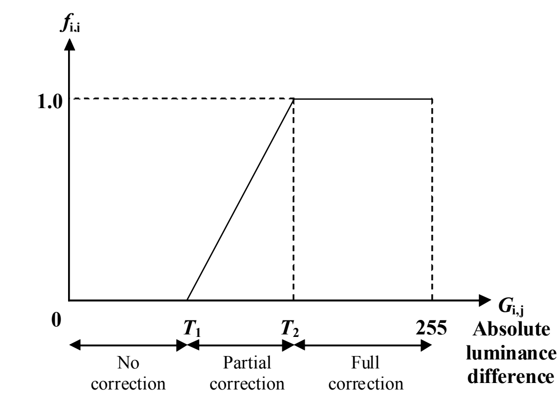


Fig. 2. Fuzzy set adopted by the fuzzy switching median filter.

B. Noise Cancellation Module

The correction term $y_{i,j}$ for replacing the current pixel $x_{i,j}$ is taken from [1], and given in (6). This correction term is also adopted by the median-based and Laplacian SM filters in [2] and [3], respectively.

$$y_{i,j} = (1 - f_{i,j})x_{i,j} + f_{i,j}m_{i,j} \tag{6}$$

where $m_{i,j}$ is the median of in the 3×3 window given by:

$$m_{i,j} = \text{median}\{x_{i-1,j-1}, \ldots, x_{i,j}, \ldots, x_{i+1,j+1}\} \tag{7}$$

The corrected pixel $y_{i,j}$ depends on a linear combination between $x_{i,j}$ and median $m_{i,j}$. The fuzzy membership value $f_{i,j}$ lends a weight on whether more of pixel $x_{i,j}$ or median pixel $m_{i,j}$ would be restored as the corrected pixel.

From the proposed algorithm, the computational time can be further decreased if the calculations involving (5) is only computed when $x_{i,j}$ is noisy. Otherwise, for noise-free $x_{i,j}$ which does not match the two salt-and-pepper noise intensities L_{upper} and L_{lower}, the fuzzy membership value is set as $f_{i,j} = 0$ and the corrected pixel $y_{i,j}$ is maintained as $x_{i,j}$.

Knowing the current pixel $x_{i,j}$ is noisy, the absolute luminance difference between the neighborhood pixels and the central pixel $g_{i+k,j+l}$ is large when the current central pixel $x_{i,j}$ is an isolated impulse in the 3×3 neighborhood. Similarly, $g_{i+k,j+l}$ is large when the current pixel $x_{i,j}$ is an edge in the image. On the other hand, the absolute luminance difference is small when any pixels in the neighborhood are also corrupted by the same salt-and-pepper noise intensities. Under these three situations, the absolute luminance difference $g_{i+k,j+l}$ could not impose an accurate correction term.

To deal with the uncertainty, we resort to fuzzy reasoning. The input variable for the fuzzy set shown in Fig. 2 is the maximum absolute luminance difference $G_{i,j}$ described in (4). The term maximum fuzzy gradient value could also be used interchangeably to describe $G_{i,j}$ as it is the fuzzy input variable using the maximum absolute luminance difference. Now, the choice in using the maximum value rather than the minimum value is a consequence from the fuzzy set adopted and the final correction term used in (6). A simple test can be performed to ensure a correct choice selection is made.

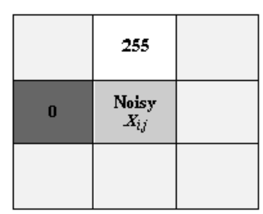


Fig. 3. The 3×3 test window corrupted with ≈30% salt-and-pepper noise.

Consider a test image degraded by a 30% salt-and-pepper noise (i.e., $p_w = p_b = 0.15$). In a 3×3 test window, there are at least 2.7≈3 pixels corrupted by salt-and-pepper noise. As previously explained, the detection method would only cancel noise if the central pixel $x_{i,j}$ is noisy. Therefore, out of the three noisy pixel, the central pixel $x_{i,j}$ in the 3×3 window is noisy, be it corrupted by a positive or negative noise pulse (see Fig. 3). The rest of the six neighborhood pixels are noise-free pixel except for the other two noisy pixels.

Assuming one of the noisy neighborhood pixels takes on intensity 255 while the one remaining noisy pixel with intensity 0, thus, the two extreme absolute luminance differences are $g_{i+k,j+l} = 0$ and $g_{i+k,j+l} = 255$. Consequently, $f_{i,j} = 0$ when the absolute luminance difference $g_{i+k,j+l} = 0$, whereas $f_{i,j} = 1$ when $g_{i+k,j+l} = 255$. The absolute luminance difference due to noise-free neighboring pixels contribute $f_{i,j}$ in the range between 0 and 1 and does not affect our test here. Using the fuzzy inference mechanism, two cases are considered:

Case1: Using minimum operator, $G_{i,j} = 0$ and $f_{i,j} = 0$.

$$y_{i,j} = (1-0)x_{i,j} + (0)m_{i,j} = x_{i,j} \tag{8}$$

In this case, the noisy pixel is restored when actually a correction is necessary.

Case 2: Using maximum operator, $G_{i,j} = 255$ and $f_{i,j} = 1$.

$$y_{i,j} = (1-1)x_{i,j} + (1)m_{i,j} = m_{i,j} \tag{9}$$

In this case, the noisy pixel $x_{i,j}$ is corrected and replaced by the median pixel of the 3×3 window.

Therefore, the maximum fuzzy gradient value $G_{i,j}$ is chosen rather than the minimum value. The abilities to preserve image details and filter salt-and-pepper noise at the edge of objects largely stem from this behavior of the FSM filter. Furthermore, the maximum operator is consistent with the fuzzy rulebase for FSM filter. The fuzzy rulebase consists of a set of rules express as the conditional IF-THEN-ELSE statements which operations are embedded in the fuzzy inference mechanism.

$$\begin{aligned}
&\text{IF}(x_{i,j} \text{ is noisy}) \text{ AND } (G_{i,j} \text{ is large})\\
&\qquad \text{THEN } (f_{i,j} \text{ is large})\\
&\text{IF}(x_{i,j} \text{ is noisy}) \text{ AND } (G_{i,j} \text{ is medium})\\
&\qquad \text{THEN } (f_{i,j} \text{ is medium})\\
&\text{IF}(x_{i,j} \text{ is noisy}) \text{ AND } (G_{i,j} \text{ is small})\\
&\qquad \text{THEN } (f_{i,j} \text{ is small})\\
&\text{ELSE } (f_{i,j} \text{ is zero})
\end{aligned} \tag{10}$$

Interpreting the fuzzy rulebase in (10), $x_{i,j}$ is noisy when it matches either L_{upper} or L_{lower}. The first rule aims at correcting an isolated impulsive $x_{i,j}$ which have a large maximum fuzzy gradient value $G_{i,j}$. The second rule processes a noisy pixel $x_{i,j}$ by performing partial correction which resulting in $x_{i,j}$ being restored as the weighted-sum of $x_{i,j}$ and the median $m_{i,j}$. This rule handles pixel at the edge of object in the image and smoothing an impulse appearing at the edge. The third rule is aimed at handling uniform area in image which is having intensities close to 0 or 255. Else, when $x_{i,j}$ is not a noisy pixel, i.e., $x_{i,j}$ does not matches the salt-and-pepper noise intensities, then $f_{i,j}$ is zero to retain $x_{i,j}$ as unprocessed. Implicitly, interpreting the fuzzy rulebase also explained the shape of the fuzzy set in Fig. 2.

III. Experimental Results

In this section, the performances of the proposed FSM filter and other methods are compared. Two 512×512 test images with 256 gray levels are used. The first image is the well known "Lena" image corrupted with 20% salt-and-pepper noise whereas the second image is the "Baboon" image corrupted with 40% salt-and-pepper noise. The feasibility of the proposed filter can be well tested and compared by considering the two images corrupted with different noise level. To measure the performance numerically, the mean square error (MSE) of the filtered image with respect to the original image is evaluated.

The simulation results for all the filters using the two different images are shown in Fig. 4 and Fig. 5. Similarly, the numerical results are tabulated in Table 1.

The filters used for comparison purposes can be divided into two classes [9]. The first class of filters belongs to the switching median (SM) filters. The salt-and-pepper noise correction for this class of filters is based on the median pixel, but the salt-and-pepper noise detection unit used distinguishes the SM filters from the classical median filter.

TABLE I
Comparison of Results for Various Methods in MSE using Images Lena Corrupted by 20% Impulse Noise and Baboon Corrupted by 40% Impulse Noise

	Lena MSE	Baboon MSE
Noisy image	3698.51	7332.24
Luo filter [1]	2094.00	6151.94
Laplacian SM 5×5 [2]	27.35	357.93
Median-based 5×5 [3]	29.97	466.73
FIRE [4]	33.94	406.24
PWL-FIRE [5]	15.10	251.36
FSM (proposed)	12.42	248.28

The median-based SM filter detect salt-and-pepper noise based on the absolute difference between a pixel and the median of a $(2N+1) \times (2N+1)$ window [3]. If the absolute difference exceeds a certain threshold, then the pixel is considered as noisy and the correction is simply replacing the noisy pixel with the median.

An extension to the median-based SM filter is the Laplacian SM filter introduced in [2]. The salt-and-pepper noise detection unit requires the image to be convolved with four one-dimensional 5×5 Laplacian operators. If the convolution sum exceeds a particular limit, then the pixel is said to be noisy. Subsequently, the noisy image will be restored with the median of a $(2N+1) \times (2N+1)$ window.

The second class of filters belongs to the fuzzy inference rule by else-action (FIRE) filters [4], [5]. This class of filters removes salt-and-pepper noise by estimating a correction term based on a set of fuzzy rulebase. The rulebase consists of different patterns for evaluating a pixel neighborhood in processing, but not all the neighboring pixels at a time. The rules fired will determine the degree to which a pixel is noisy based on the fuzzy membership value calculated from the fuzzy sets used. An appropriate correction term is then calculated to replace the noisy pixel.

Fig. 4. The 512×512 Lena test image; (a) original image, (b) original image corrupted by 20% salt-and-pepper noise, and the rest are results of the filtered image by various techniques: (c) Luo filter, (d) Median-based SM 5×5, (e) Laplacian SM 5×5, (f) FIRE, (g) PWL-FIRE, and (h) FSM.

The differences between the FIRE and piecewise-linear FIRE (PWL-FIRE) filters are the choice of fuzzy sets and the neutralization of small corrections [10]. The PWL-FIRE filter uses not one, but two piecewise-linear fuzzy sets instead of one triangular shape fuzzy set as adopted by FIRE filter. Secondly, for small corrections, it is implicitly avoided through the choice of the two piecewise-linear fuzzy sets rather than being performed explicitly.

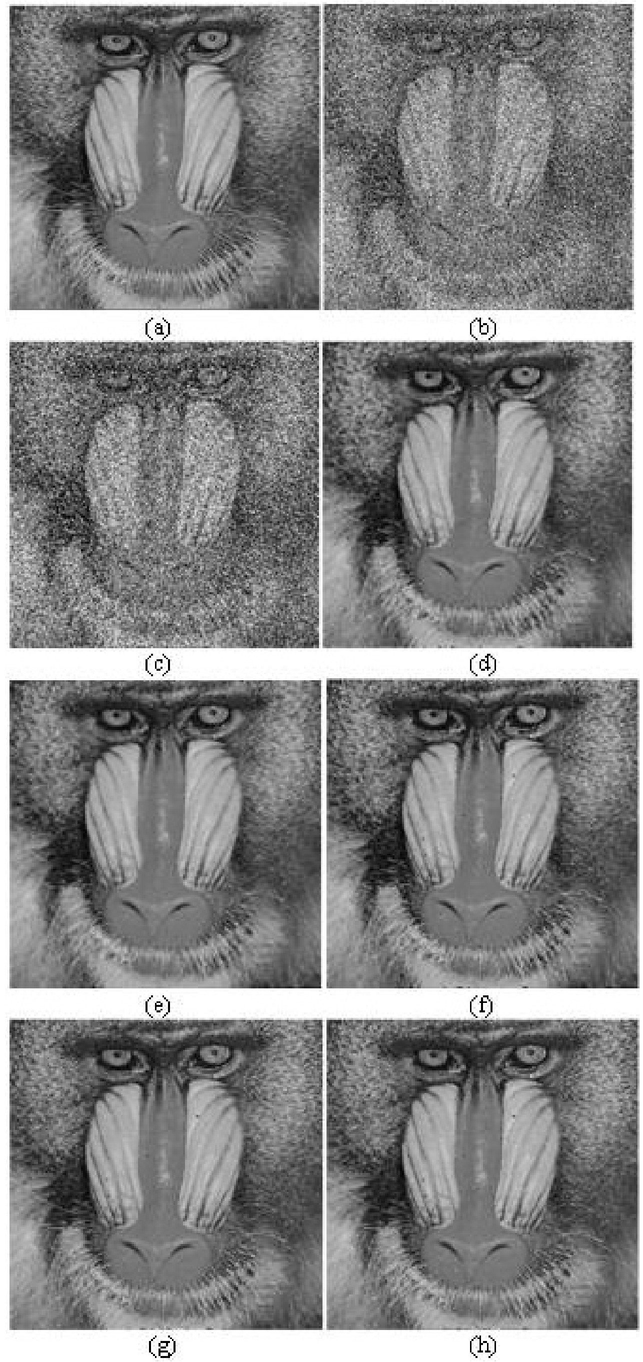


Fig. 5. The 512×512 Baboon test image; (a) original image, (b) original image corrupted by 40% salt-and-pepper noise, and the filtered images of different methods in comparison: (c) Luo filter, (d) Median-based SM 5×5, (e) Laplacian SM 5×5, (f) FIRE, (g) PWL-FIRE, and (h) FSM.

By visually interpreting the results obtained, for low level salt-and-pepper noise, Fig. 3 shows most filters perform equally well except for Luo filter proposed in [1]. When the image is corrupted with 40% salt-and-pepper noise as shown in Fig. 4(b), Luo filter only managed to remove a small portion of the noise. The 5×5 Laplacian SM filter could perform better than the median-based SM filter at this noise level. However, the filtered image of the median-based filter is blurred while the 5×5 Laplacian SM filter leaves impulse appearing at image fine details to be unprocessed. This is because the "Baboon" image contains a lot of small details. When filtered using median-based filter, most of the pixels, even the noise-free pixels are tend to be detected as the noisy pixels, and replaced by the median value. The 5×5 Laplacian SM, on the other hand, is designed to preserve lines and edges, and thus has a better salt-and-pepper detection in this type of data.

The PWL-FIRE filter is able to perform better than the conventional FIRE filter in the sense more noise patches are removed by the PWL-FIRE filter. Nonetheless, a close inspection on the filtered image in Fig. 4(g) indicates there is still noise left unfiltered at the region having the image fine details. The texture of the image has been altered as well after filtering action by the PWL-FIRE filter. It is in these two respects; the ability to remove impulses present at high frequency components of image at the same time preserving the texture that the proposed FSM filter outperforms the other filtering methods. The MSE reported in Table 1 shows the filtered image of FSM filter has the lowest MSE value. As image is subjective to the human eyes, close comparison on the filtered image in Fig. 4(h) to the original image in Fig. 4(a) indicates the proposed FSM filter is able to preserve image fine details and textures very well after the salt-and-pepper noise has been removed.

The effect of thresholding T_1 and T_2 on the performance of the FSM filter is not significant as long as T_1 and T_2 lies in a range that covers the switching of a pixel that is regarded as noisy or noiseless. The optimized values of T_1 and T_2 for the fuzzy set in Fig. 1 are $T_1 = 10$ and $T_2 = 30$. However, doubt arises when the difference between T_1 and T_2 is small. One may think that the small differences would eventually make the FSM filter to behave like a classical 3×3 median filter, i.e., a noisy pixel is replaced by its median pixel. But this is not the case when tested with the image in Fig. 3(b). The MSE of the filtered image by a 3×3 basic median filter is 189.68 while the MSE for image filtered using the FSM filter is only 12.42.

During the filtering action, the FSM filter is applied recursively. A recursive filter replaces the current pixel with the filtered pixel once the current pixel is processed [10]. In other words, the filtering action for next pixels would use the values of the previously filtered pixel in its calculations. In this paper, the class of SM filters is not recursive while the class of FIRE filters is recursive filters. Using the filtered pixel value in evaluation of unfiltered pixels would yield a more accurate result provided the previously filtered pixels are restored correctly.

IV. Conclusion

This paper presented a recursive fuzzy switching median filter which is an extension to the classical switching median filter by employing fuzzy inference mechanism. Simulation results show FSM could remove noise while preserving image details and textures very well. It is suitable to be applied in consumer electronics such as digital camera due to its simple and low complexity algorithm. Unlike some filtering mechanisms which require iterations, and thus consumed lengthy processing time, the FSM filter only need to be applied once and is very efficient with its computational time.

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