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An Efficient Adaptive Fuzzy Switching Weighted Mean Filter for Salt-and-Pepper Noise Removal

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Abstract--- An image degraded by noise is a common phenomenon. In this letter, we propose a novel adaptive fuzzy switching weighted mean filter to remove salt-and-pepper (SAP) noise. The process of denoising includes two stages: noise detection and noise elimination. In the first stage, pixels in a corrupted image are classified into two categories: original pixels and possible noise pixels. For the latter, we compute the maximum absolute luminance difference of processed pixels next to possible noise pixels to classify them into three categories: uncorrupted pixels, lightly corrupted pixels, and heavily corrupted pixels. In the second stage, under the assumption that pixels at a short distance tend to have similar values, the distance relevant weighted mean of the original pixels in the neighborhood of a noise pixel are computed. For a non-noise pixel, retain it as unchanged; for a lightly corrupted pixel, replace it with the weighted average value of the weighted mean and its own value; and for a heavily corrupted pixel, change it to be the weighted mean. Experimental results show that compared to some state-of-the-art algorithms, our method keeps more texture details and is better at removing SAP noise and depressing artifacts.

Index Terms--- Fuzzy Switching Weighted Mean Filter, Maximum Absolute Luminance Difference (ALD), Noise Detection, Noise Elimination, Salt-and-Pepper (SAP) Noise.

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I. INTRODUCTION

Image denoising is one of the earliest image processing tasks, and it is usually an essential stage for many image-processing methods, such as image super resolution, pattern recognition, and image fusion. Images are usually degraded by noise in the process of acquisition and transmission. Salt-and-pepper (SAP) noise is quite common in natural images, with maximum and minimum intensities. In an 8-bit gray level image, this appears as white and black points that resemble “salt” and “pepper,” respectively. SAP noise is generated mostly during the process of image capture and storage, due to false locations in memory and damaged image sensors [1].

There are many studies that have put forth methods to remove SAP noise [2]–[6]. Median filter (MF) and adaptive MF (AMF) [7] are two methods applied during an early stage to reduce SAP noise. MF is widely used due to computational convenience, but it does not distinguish between noiseless and noise pixels, and all pixels are replaced with neighborhood median pixels. AMF is a development of MF, and in AMF, original pixels and noise pixels are differentiated, with only noise pixels being replaced. Additionally, there is an adaptive changeable size of a neighborhood factor applied to find a non-noise median pixel. However, when the image has a high noise ratio, a pixel might be replaced with a pixel with a far distance, and this will cause a loss in image detail and bring about an artifact.

In [8], a modified AMF is proposed to constrain the maximum size of the window to avoid having a median pixel too far from the center, and the remaining noise pixels are filtered in the second processing without a window size limit. In [9], a classified MF is proposed to cut down the processing time. When the noise ratio is not more than 50%, only pixels along the direction of the vertical and horizontal are considered. A mean filter is widely used to eliminate Gaussian noise. [7], [10], [11]. In [12], a weighted mean filter is used to reduce

SAP noise. In the method, all the weights of nonnoise pixels are set to be the same value. As such, this may smooth out many details. In [13], an impulse detector is proposed to detect random value impulse. Luo [14] develops the method in [13], and uses a fuzzy algorithm for impulse noise reduction. In [15], a maximum absolute gradient method is proposed to detect SAP noise. In [1], Toh and Isa combines the method in [15] with AMF that can effectively decrease SAP noise.

In this letter, the main contribution is a novel adaptive fuzzy switching weighted mean filter proposed to remove SAP noise. First, a more accurate mathematical expression for SAP noise is given. Second, an improved maximum absolute luminance difference (ALD) method is proposed to detect SAP noise more accurately. Finally, combined with fuzzy algorithm, a distance relevant method is proposed to compute the weighted mean, which can keep the edges better.

The rest of the letter is organized as follows. In Section II, a de-tailed description of our proposed method is given. In Section III, the experimental results and comparisons with some existing methods are shown. Finally, the work is concluded in Section IV.

II. OUR PROPOSED METHOD

This section details our method for utilizing an adaptive fuzzy switching weighted mean filter. SAP noise is a kind of important impulse noise, which has fixed values at a maximum and minimum in the image. Let x be the original clean image, and y is the image corrupted by SAP noise. In an 8-bit gray-level corrupted image, the value of a "salt" pixel is $I_{salt} = 255$, the value of a "pepper" pixel is $I_{pepper} = 0$, and others are in the range of [0 255]. In typical mathematical expression of SAP noise, all pixels with maximum (minimum) value are set to be noise [12]. This expression is inaccurate because these pixels may also be details. To solve this problem, a model is given as follows:

$$y_{i,j} = \begin{cases} \text{SAP noise} & \text{with probability } p \\ x_{i,j} & \text{with probability } 1-p \end{cases} \tag{1}$$

where $y_{i,j}$ and $x_{i,j}$ are pixels at location (i,j) of a corrupted image and its original image, p is the probability of noise pixels. In expression (1), we use SAP noise rather than 0 or 255 to express noise pixels. This is a more accurate expression.

SAP Noise Detection

Let $Y\max$ and $Y\min$ denote the maximum and minimum values of y, respectively, where we use a binary matrix S to record the locations that are $Y\max$ and $Y\min$ or not

$$S_{i,j} = \begin{cases} 0, & y_{i,j} = Y\max \text{ or } y_{i,j} = Y\min \\ 1, & \text{otherwise.} \end{cases} \tag{2}$$

where S_{ij} is the value of location (i, j) of binary matrix S. $S_{i,j} = 0$ means $y_{i,j}$ is possible SAP noise, and $S_{i,j} = 1$ means $y_{i,j}$ is noiseless. For a natural image, large value pixels commonly include information for texture details, so it is necessary to further identify the maximum (minimum) value pixels as noise or not. Some detection methods use the maximum ALD of the pixel and pixels in its neighborhood to identify them, but they do not differentiate noise pixels and nonnoise pixels in the neighborhood. This may cause the noiseless pixels to be mistaken for noise pixels as the neighborhood may include maximum pixels in the opposite intensity direction, especially when the noise ratio level is high. To solve this problem, we improve the method in [1]. We assume processed pixels are noiseless, and propose to use only processed pixels to compute the maximum ALD. This effectively avoids mistaking uncorrupted pixels and lightly corrupted pixels from heavily corrupted pixels. For the pointwise mode of processing, when we process pixel $y_{i,j}$,pixels above it and pixels at the left of the same line, all have been treated. Let h denote the partly processed image of y, the processed pixels set Ω next to $y_{i,j}$ can be represented as

$$\Omega = \{h_{i-1,j-1}, h_{i-1,j}, h_{i-1,j+1}, h_{i,j-1}\} \quad (3)$$

where $h_{i,j}$ is the element of h. The ALD of $y_{i,j}$ and pixels in Ω can be described as

$$\text{ALD} = |h_{k,l} - y_{i,j}|, \; h_{k,l} \in \Omega. \quad (4)$$

The maximum value of ALD is defined as

$$\text{M-ALD} = \max\{\text{ALD}\}. \quad (5)$$

In a natural image, pixels are supposed to change smoothly, and adjacent pixels tend to have similar values. For an image that is degraded by SAP noise, the value of partial pixels are changed to maximum (minimum), and the values of pixels may suddenly change. In this letter, only processed pixels are used to compute the M-ALD, which effectively avoids unprocessed pixels as noise causes the sudden change. M-ALD of a large value implies pixels are noise, and a small value indicates the pixels are noiseless.

After the computation of M-ALD, two thresholds are introduced to classify maximum (minimum) value pixels into three categories: uncorrupted pixels, lightly corrupted pixels, and heavily corrupted pixels. The fuzzy flag $L_{i,j}$ is used to indicate a pixel as one of the three categories:

$$L_{i,j} = \begin{cases} 0, & \text{if M-ALD} \le D1 \\ \frac{\text{M\_ALD} - D1}{D2 - D1}, & \text{if } D1 < \text{M-ALD} < D2 \\ 1, & \text{if M-ALD} \ge D2 \end{cases} \quad (6)$$

where $D1$ and $D2$ are two predefined thresholds. $L_{i,j} = 0$ means $y_{i,j}$ is an uncorrupted pixel, $0 < L_{i,j} < 1$ indicates y_{ij} is a lightly corrupted pixel, and $L_{i,j} = 1$ implies $y_{i,j}$ is a heavily corrupted pixel.

SAP Noise Elimination

For many MF methods, after noise detection, noise pixels are replaced with pixels of a median value from their neighborhoods. When the radius of a neighborhood is large, the median value pixel may have a long distance from the center. In this condition, the difference of the median value pixel and the original pixel that is noiseless in the center may be large, and that would cause the denoised image to be degraded. In [12], the median value is substituted for a weighted mean to replace the noise pixel. But in that work, all the pixels used to estimate the weighted mean are set to be the same weights, which may cause the details to be smoothed out. To tackle this problem, we fully consider the factor of distance, and implement a distance relevant adaptive fuzzy switching mean filter to remove SAP noise. In our method, only nonmaximum and nonminimum (NN) pixels are chosen to compute the distance relevant weighted mean.

Let $W_r(i, j)$ denote a window, whose center is at location (i, j) with a radius of r:

$$W_r(i, j) = \{(k, l) | r \ge |k - i|, |l - j| \le r. \quad (7)$$

In order to make the neighborhood have NN pixels, for binary image S, compute the sum of elements in window $W_r(i, j)$:

$$\xi = \sum_{k,l} S_{k,l}, \; (k, l) \in W_r(i, j). \quad (8)$$

If $\xi > 0$, the window has NNpixels, otherwise enlarge the radius of the window until a NN pixel appears or the radius reaches to the predetermined maximum value R_{max}. If the radius of a window is less than the predetermined maximum value, i.e., $r < R_{max}$, the window has NN pixels. Our definition of weight considers the factor of distance, which means pixels far from the center will have a smaller weight while others will have a larger weight.

The mathematical expression of weight is described as follows:

$$w_{kl,ij} = \begin{cases} 1/(k-i)^2 + (l-j)^2, & (k,l) \ne (i,j) \\ 0, & (k,l) = (i,j) \end{cases} \quad (9)$$

where $w_{kl,ij}$ is the weight of pixel $y_{k,l}$ with respect to pixel $y_{i,j}$. From (9), we find that the value of $w_{kl,ij}$ decreases as distance increases, and pixels in a vertical and horizontal direction have a larger weight than pixels in diagonal direction because they have a shorter distance. In our algorithm, only NN pixels are chosen to evaluate the value of the center pixel, and the weight corresponding to others are set to zero:

$$T = WS * Ww \quad (10)$$

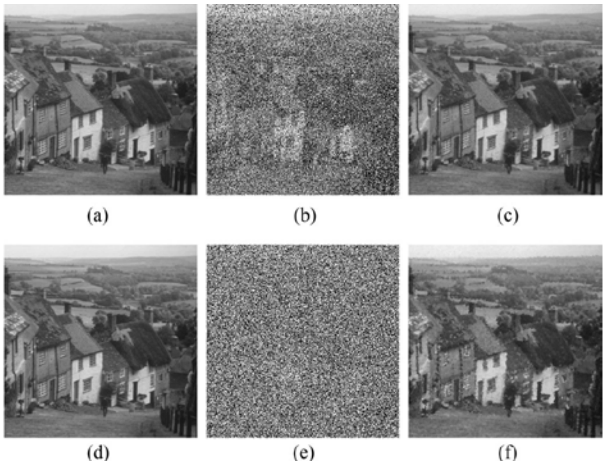

Fig. 1: Experimental Results for "hill" with SAP Noise Ratio of 50% and 90% (a) Original Image (b) Noise Ratio 50%. (c)De-noised Image (d) Original Image (e) Noise Ratio 90%. (f) De-noised Image

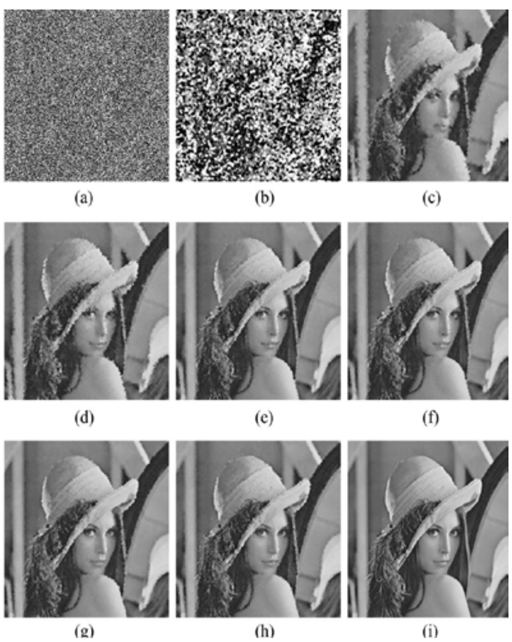

Fig. 2: Experimental Results of Several Methods for "Lena" of size 512 × 512 with SAP Noise Ratio of 90%

The PSNR and SSIM are (a) Noised image(5.8985 dB, 0.0292). (b) MF (8.5278 dB, 0.0533). (c) AMF (22.1784 dB,0.7621). (d) NRIPN (23.0461 dB, 0.7929). (e) NAFSMF (25.9625 dB, 0.8731).(f) FEMF (26.0554 dB, 0.8736). (g)AWMF(26.1230 dB, 0.8730). (h) Proposed method (26.3297 dB, 0.8749). (i) Original image. where T is the weight matrix corresponding to NN pixels; WS and Ww are the windows of binary matrix S and weight matrix with radius r, respectively; and symbol*is the Hadamard product. The distance relevant weighted mean of NN pixels is depicted as follows:

$$\text{Ymean} = \frac{\sum_{k,l=1}^{r} T*Wy}{\sum_{k,l=1}^{r} T} \qquad (11)$$

where Wy denotes that the window centers at yi,j of radius r. The denominator is used for normalization.

If the radius of the window is equal to the predetermined maximum value, i.e., $r = R\text{max}$, the window may not have NN pixels. The weighted mean is estimated by the mean of proceeded pixels next to the center

$$Y\text{mean} = (hi-1,j-1 + hi-1,j + hi-1,j+1 + hi.j-1)/4. \qquad (12)$$

The original clean pixel is estimated with a fuzzy switching method:

$$Xi,j = (1 - Li,j\,)yi,j + Li,j\ Y\text{mean} \qquad (13)$$

where $\hat{x}_{i,j}$ is the evaluation of original clean pixel $x_{i,j}$. From (13), we find that if $y_{i,j}$ is an uncorrupted pixel, the evaluated original pixel $\hat{x}_{i,j}$ is kept the same; if $y_{i,j}$ is a lightly corrupted pixel, $\hat{x}_{i,j}$ is the weighted mean of y_{mean} and $y_{i,j}$; and if $y_{i,j}$ is a heavily corrupted pixel, it is replaced with y_{mean}.

III. EXPERIMENTAL RESULTS AND COMPARISONS

This section illustrates the effectiveness of our proposed method, and the results are compared with six existing algorithms: MF, AMF [7], new algorithms for recovering highly corrupted images with impulse noise (NRIPN) [8], noise adaptive fuzzy switching median filter (NAFSMF) [1], fast and efficient median filter (FEMF) [9], and adaptive weighted mean filter (AWMF) [12]. Twelve typical images are chosen for the tests. Images for each dimension include 512 × 512 images consisting of "Lena," "boat," "Barbara," "hill," "couple," and "pentagon"; 256 × 256 images consisting of "monarch," "house," "peppers," "bridge," and "parrot"; and a 479 × 479 image consisting of "aerial." Two typical image quality metrics, peak signal-to-noise ratio (PSNR) [16] and structural similarity (SSIM)

[17] are employed to verify the quality of the experimental results. PSNR is defined as

$$PSNR = 10 \log_{10}(225^2/MSE) \quad (14)$$

where MSE is the mean square error of two images, which can be expressed as

$$\text{MSE}= 1/(\text{M*N}) \sum_{i=1}^{m} \sum_{j=1}^{n} (xi,j - yi,j)^2$$

where $x_{i,j}$ and $y_{i,j}$ are pixels of image x and y of size $M \times N$ respectively. SSIM is defined as

$$\text{SSID} = \frac{(2\mu x\mu y + c1)\,(2\sigma xy + c2)}{(\mu x^2 + \mu y^2 + c1)\,(\sigma x^2 + \sigma y^2 + c2)} \quad \textbf{(15)}$$

where μ_x and μ_y are the average intensities of x and y, respectively. σ_x and σ_y are standard deviations, $\sigma_{x\,y}$ is the covariance, c_1 and c_2 are some constants, as in [17], and c_1 and c_2 are set to be $(0.01 \times 255)^2$ and $(0.03 \times 255)^2$, respectively. The experiments are performed in MATLAB R2014a with a Windows 7 operating system with 2 GB memory and an Intel Core 2 Duo CPU E8400@3.00 GHz.

In this letter, as in [1], we set $D_1 = 10$, $D_2 = 30$, and R_{max} =39. Fig. 1 shows the experimental results of the image "hill" with a SAP noise ratio of 50% and 90%, respectively. The algorithm can effectively suppress the noise even at high noise ratios and performs well in maintaining edges in the process of denoising. Fig. 2 shows the denoised images of "Lena" for several methods with a noise ratio of 90%. Fig. 2(a) is an image with noise, where it is difficult to observe any details; MF is the simplest filter, but it does not work well with such a high noise ratio; Fig. 2(h) is the result of our proposed method, and gives better visual result than the other six methods. From a quantitative perspective, our method has the highest value for the image quality metrics of PSNR and SSIM. Fig. 3 shows the local features of the "parrot" image for several filters with a SAP noise ratio of 80%. The figure shows that the MF method causes the severest edge lost, and it is difficult to determine any notable edges. AWMF obtains the closest results to our algorithm, but our restored image contains more details. Table I shows the mean value of PSNR for the 12 images with different noise ratio.

Table I: Mean PSNR of Several Algorithms for the 12 Traditional Images with Different SAP Noise Ratios

Algorithm	30%	50%	70%	90%
MF	24.2872	23.1701	17.7915	8.3669
AMF	29.0369	26.1860	23.1091	19.4996
NRIPN	29.6017	26.3057	23.3563	20.1436
NAFSMF	31.3967	28.3620	25.8308	22.3242
FEMF	31.8732	28.4005	25.8360	22.4026
AWMF	31.0221	28.6905	24.1467	22.4921
Proposed method	32.1601	29.1793	26.3755	22.6252

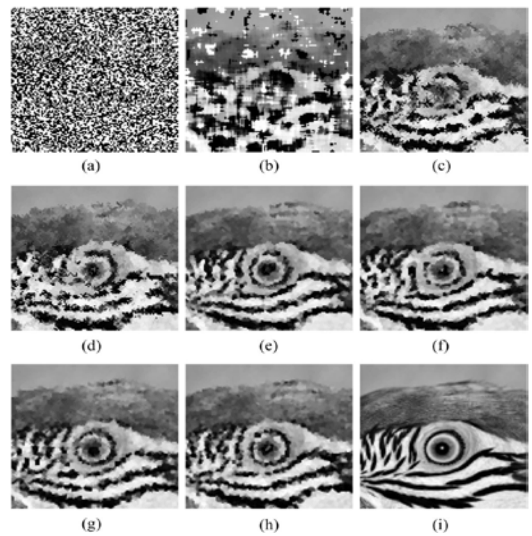

Fig. 3: Comparison of local features for image "parrot" with noise ratio of 80% with several methods. The PSNR and SSIM are (a) Noise image (5.8097 dB, 0.0519). (b) MF (9.6371 dB, 0.1825). (c) AMF (13.4334 dB, 0.5207). (d)NRIPN (13.4012 dB, 0.5070). (e) NAFSMF (16.1691 dB, 0.6818). (f) FEMF (16.0472 dB, 0.6753). (g) AWMF (16.3780 dB, 0.6877). (h) Proposed method (16.7923 dB, 0.6987). (i) Original image

MF has the smallest values, AWMF is nearest to our proposed method, and our method obtains the highest PSNR values. Table II gives the mean value of SSIM for the 12 images with different noise ratios. The results are similar to those of PSNR, with our method also obtaining the best SSIM results. Fig. 4 shows the average processing time for 12 images with different SAP noise ratios for seven methods: MF, AMF, NRIPN, NAFSMF, FEMF, AWMF, and the proposed method. MF uses the least time among all the methods, but has the worst quality. NRIPN used less time than our method when noise ratio is less than 70%, but when noise ratio is above 70%, we used lesstime, and our method has much better restoration quality with respect to all noise ratios. Furthermore, our method consumes less time than the other four methods. AWMF obtains the most approximate restoration quality as compared to our method, but it consumes much more time.

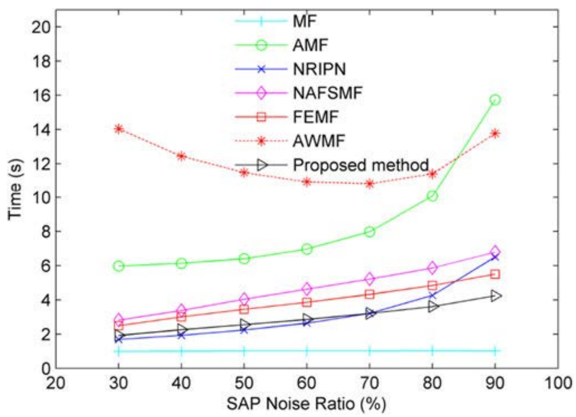

Table II: Mean SSIM of Several Algorithms for the 12 Traditional Images with Different SAP Noise Ratios

Algorithm	30%	50%	70%	90%
MF	0.7577	0.7256	0.4887	0.0514
AMF	0.9416	0.8921	0.8017	0.5909
NRIPN	0.9540	0.8794	0.8026	0.6226
NAFSMF	0.9663	0.9307	0.8744	0.7313
FEMF	0.9698	0.9321	0.8742	0.7329
AWMF	0.9650	0.9343	0.8786	0.7352
Proposed method	0.9703	0.9386	0.8858	0.7358

IV. Conclusion

This letter proposes a new two stages adaptive fuzzy switching weighted mean filter to remove SAP noise. In the first stage, an improved maximum ALD is used to classify pixels into three categories: uncorrupted pixels, lightly corrupted pixels, and heavily corrupted pixels. In the second stage, for each type of pixel, a distance relevant adaptive fuzzy switching weighted mean filter is used to eliminate noise. The experimental results show that compared with several existing algorithms, our method obtains the best results and uses less processing time than most other methods.

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