Simple Adaptive Median Filter for the Removal of Impulse Noise from Highly Corrupted Images

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Abstract — *This paper presents a simple, yet efficient way to remove impulse noise from digital images. This novel method comprises two stages. The first stage is to detect the impulse noise in the image. In this stage, based on only the intensity values, the pixels are roughly divided into two classes, which are "noise-free pixel" and "noise pixel". Then, the second stage is to eliminate the impulse noise from the image. In this stage, only the "noise-pixels" are processed. The "noise-free pixels" are copied directly to the output image. The method adaptively changes the size of the median filter based on the number of the "noise-free pixels" in the neighborhood. For the filtering, only "noise-free pixels" are considered for the finding of the median value. The results from 100 test images showed that this proposed method surpasses some of the state-of-art methods, and can remove the noise from highly corrupted images, up to noise percentage of 95%. Average processing time needed to completely process images of 1600×1200 pixels with 95% noise percentage is less than 2.7 seconds. Because of its simplicity, this proposed method is suitable to be implemented in consumer electronics products such as digital television, or digital camera[1].*

Index Terms — Noise reduction, salt-and-pepper noise, impulse noise, median filter, adaptive filter

I. INTRODUCTION

Digital images, which are a subset to digital signals, are normally corrupted by many types of noise, including impulse noise [1]. Impulse noise, even with a low noise percentage, can change the appearance of the image significantly. This is because, the impulse noise, which is a set of random pixels, normally has a very high contrast to its surrounding [2],[3].

Malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission of the image in a noisy channel, are some of the common causes for impulse noise [4]. The amplitude of the corruption is relatively very large compared with the strength of the original signal. As a consequence, when the signal is quantized into L intensity levels, the corrupted pixels are generally digitized into either two extreme values, which are the minimum or maximum values in the dynamic range (i.e. 0 or L-1). For this reason, impulse noise normally appears as white or black dots in the image, thus also referred as salt-and-pepper noise [1],[4].

Median filter is one of the order-statistic filters, which falls in the group of nonlinear filter. Median based filters are the popular methods to be employed for reducing the impulse noise level from corrupted images. This is because of their simplicity and capability to preserve edges [5]. The conventional median works in spatial domain, and based on windowing process, using a filter size of $W_M \times W_N$. Normally W_M and W_N are both in odd dimensions.

Given an input image f, the filtered image g is defined by:

$$g(x,y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{f(s,t)\} \tag{1}$$

where (x,y) are the coordinates of the pixel located at the center of the contextual region S_{xy} defined by $W_M \times W_N$, and (s,t) are the coordinates of the pixels belong to that region. This means that filtered pixel is the median value of the data contained in the contextual region [1],[2].

The conventional median filter method, as defined in (1), processes all pixels in the image equally, including the "*noise free pixels*". This will result the elimination of fine details such as thin lines and corner, blurring, or distortion in the images [6],[7]. Thus, many variations and improvements of median filter have been introduced. Works in [3]-[18] are some of the examples. However, not all of these methods are suitable to be implemented in consumer electronics product. For example, work in [4] and [5] may not be fit to be implemented in consumer electronics products due to their complexity and long processing time.

One of the branches of median based filter is the adaptive median filter, such as the work by [4] and [18]. The size of the median filter applied to the individual pixel is determined based on the approximation of the local noise level. Bigger filter is applied to the areas with high level of noise, and smaller filter is applied to the areas with low level or noise. Work by Hwang and Haddad [18], for example, approximate the "*noise pixels*" based on the minimum, maximum and median intensity values contained inside a local window. They started with a smaller window size first, and increase the size until certain conditions are met.

Another type of the median based methods is the switching method, which is constructed from two stages. The first stage in these methods is normally to detect the "*noise-pixel*". The second stage is to remove the noise. In this stage, only "*noise-*

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pixels" are filtered using (1). Other pixels, which are considered as "*noise-free pixels*", are kept unchanged.

One of the works in this framework is the work by Zhang and Karim [8]. The main aim of their work is to prevent median filter from altering fine details, especially the thin lines, in the image. To obtain this, they first convolve the corrupted image with a set of 5×5 convolution kernels that are based on Laplacian operator, to find the value of temporary parameter r for each pixel location in the image. Parameter r shows how likely a pixel is an impulse noise. Their convolution kernels are specially designed to give a high value of r for stray impulse pixels, and low value of r when an edge in certain directions is detected. The value of r is then compared with the predefined threshold value T. If r is less than T, this means that the intensity of the current pixel is similar to the surrounding intensity values. Under this condition, the pixel is considered as a "*noise-free pixel*", thus the pixel value is copied directly to the output image. On the other hand, if r is greater than T, the pixel is considered as a "*noise-pixel*". This pixel is then filtered by a median filter of size $W_M \times W_N$, using (1). Zhang and Karim claimed that their method is better than the works in [9]–[11].

Luo [7] has proposed a simple switching median filter based on fuzzy impulse detection technique. First, the method finds the two peaks from the histogram to approximate two intensity values that present the impulse noise. Pixels with these intensity values become the candidates for the impulse noise. For each candidate, the minimum absolute intensity difference between a pixel with its eight-neighbors in a 3×3 window is determined. This minimum value is assigned to the value of r, a parameter that indicate how likely the pixel to be an impulse noise. The minimum value is selected in order to preserve the fine details in the image. Then, based on the value of r and two predefined threshold values, $T1$ and $T2$ (i.e. $T1 < T2$), the pixels are grouped into three groups, which are; "*noise-free pixels*", "*noise-pixels*", and "*possibly noise-pixels*". The filtering is only carried out to the "*noise-pixels*" and "*possibly noise-pixels*". For the "*noise-pixels*", filtering in (1) is carried out. For the "*possible noise-pixels*", the median value based on (1) is first determined, and then this value is recombined with the intensity of the image, using a weighting value that is calculated based on a fuzzy membership function. The method is claimed to have a better performance than the methods proposed in [9]–[17].

In this paper, we present a new median filter based technique, which is a hybrid of adaptive median filter and switching median filter. This proposed method is fast, simple, and adaptable to the local noise level. The method can remove the impulse noise effectively from the image, and at the same time can preserve the details inside the image, even when the input image is very highly corrupted by the noise. The method is also does not require any parameter to be tuned, thus suitable for an automated system. Similar to [5], the method does not need previous training.

This paper is organized as follows. Section II describes the proposed method in details. Section III presents our results and discussions. Section IV concludes the paper.

II. The Proposed Method

Our proposed method is a hybrid of adaptive median filter with switching median filter. We use the adaptive median filter framework in order to enable the flexibility of the filter to change it size accordingly based on the approximation of local noise density. We use switching median filter framework in order to speed up the process, because only the noise pixels are filtered. In addition to this, switching median filter also allows local details in the image to be preserved.

We divide this method into two stages, which are the noise detection, and the noise cancellation. These two methods are described in the following subsections. In order to implement this method, we need three 2D arrays of the same size to hold the pixel values of the input image f, the output image g, and the mask to mark the "*noise pixels*" α. The dimensions of these arrays are equal to the dimensions of f (i.e. $M \times N$).

A. Stage 1: Noise Detection

There are two main purposes of this stage. The first one is to identify the "*noise pixel*", and the second one is to roughly approximate the noise level of the image.

Luo [7] has use the histogram of the input image to find two intensity values that presents the impulse noises. The identification is based on the peak values contained in the histogram. He assumes that the bright and dark intensity values of the impulse noise produce two peaks in the histogram. However, in our method, we do not use this assumption because this statement is not always true, especially when the input is only corrupted by low level of noise.

Based on [1] and [4], we assume that the two intensities that present the impulse noise are the maximum and the minimum values of the image's dynamic range (i.e. 0 and L-1). Thus, in this stage, at each pixel location (x,y), we mark the mask α by using the following equation:

$$\alpha(x,y) = \begin{cases} 1 & : \quad f(x,y) = L-1 \\ 1 & : \quad f(x,y) = 0 \\ 0 & : \quad \text{otherwise} \end{cases} \tag{2}$$

where the value 1 presents the "*noise pixel*" and the value 0 presents the "*noise-free pixel*".

Next, after we classify the pixels using (2), we calculate the total number of the "*noise pixel*", K. This is given by (3).

$$K = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \alpha(x,y) \tag{3}$$

Using the value of K, we can roughly estimate the impulse noise level η that corrupts the image. The value of η is the ratio of the "*noise pixels*" to the total number of pixels contained in the image, as defined in the following equation:

$$\eta = K/(MN) \tag{4}$$

The value of η is in between 0 and 1 (i.e. $0 \le \eta \le 1$). This value and the noise mask α will be used in the following stage, which is for the noise removal.

B. Stage 2: Noise Cancellation

In this stage, we filter the input image f, and produce the filtered image g. Similar to many switching median filter methods, the output is defined as:

$$g(x,y) = [1-\alpha(x,y)]f(x,y) + \alpha(x,y)m(x,y) \tag{5}$$

where α is the noise mask, defined by (2) in Stage 1, where m is the median value obtained from our adaptive method. The determination of m will be explained later.

As $\alpha(x,y)$ only can take value of either 0 or 1, as defined by (5) the output value $g(x,y)$ is either equal to $f(x,y)$ or $m(x,y)$. Thus, the calculation of $m(x,y)$ is only done when $f(x,y)$ is a "*noise pixel*" (i.e. $\alpha(x,y) = 1$). For the "*noise-free pixel*" (i.e. $\alpha(x,y) = 0$), the value of $f(x,y)$ is copied directly as the value of $g(x,y)$. This significantly speeds up the process, because not all pixels need to be filtered. Thus, alternatively, $g(x,y)$ can be re-written as:

$$g(x,y) = \begin{cases} f(x,y) & : \quad \alpha(x,y) = 0 \\ m(x,y) & : \quad \text{otherwise} \end{cases} \tag{6}$$

We use the adaptive methodology to determine $m(x,y)$. This means that the size of the filter used at every pixel location is changing accordingly to the local information. In this work, we only consider the square filters with odd dimensions for the filtering process, as given by (7).

$$W = W_M = W_N = 2R + 1 \tag{7}$$

where R takes any positive integer value.

Our method, similar to the method proposed in [5], uses only "*noise-free pixels*" that are contained in the contextual region, defined by the area of $W\times W$ (i.e. the filter size), as the samples for the calculation of $m(x,y)$. This procedure ensures that the value of $g(x,y)$ will not be affected by the noise, but be more biased towards the real data values.

However, unlike the method in [5] that uses a fixed size of filtering window, our method is an adaptive, where the size of the filter is not fixed. To determine the value of $m(x,y)$, in our proposed method, we set a rule that the minimum number of samples of "*noise-free pixels*" needed for this calculation must be greater or equal to eight pixels. If a small sample size is taken, where the total samples are less than eight samples, these samples are not good enough to present the local information of the image properly. If a large sample size is taken, this also cannot present the local information because the samples come from many objects in the image. Thus, a large sample size, although requires more computational time, tends to introduce distortions because of this reason.

Our novel adaptive method for finding $m(x,y)$ is described by the following algorithm. For each pixel location (x,y) with $\alpha(x,y)=1$ (i.e. "*noise pixel*"), do the following:

1. Initialize the size of the filter $W = 2R_{\min}+1$, where $R_{\min}$ is a small integer value.
2. Compute the number of "*noise-free pixels*" contained in the contextual region defined by this $W\times W$ filter.
3. If the number of "*noise-free pixels*" is less than eight pixels, increase the size of the filter by two (i.e. $W = W+2$) and return to step 2.
4. Calculate the value of $m(x,y)$ based on the "*noise-free pixels*" contained in $W\times W$ window.
5. Update the value of $g(x,y)$ using either (5) or (6).

In order to minimize the number of trials needed to find the correct filter size, the value of $R_{\min}$ in the first step in the algorithm can be approximated using (8).

$$R_{\min} = \left\lfloor \frac{1}{2}\sqrt{\frac{7}{1-\eta}} \right\rfloor \tag{8}$$

where $\lfloor Z \rfloor$ presents the floor value of Z (e.g. if $Z = 2.05$, then $\lfloor Z \rfloor = 2$). By using $R_{\min}$ as defined in (8), this will allow the algorithm to converge faster, because less looping is needed to find the correct size W for the window. As the consequence, this will speed up the process.

III. Experimental Results

In order to demonstrate the performance of our method, we also implemented three other median filtering methods. As our method is a hybrid of an adaptive median filter and a switching median filter, we implemented the methods proposed by Luo[7], Zhang and Karim[8], and Hwang and Haddad [18]. Methods [7] and [8] are switching median methods, while method [18] is an adaptive median method. For the implementation of [7], we set the threshold values $T1$ equal to 10 and $T2$ equal to 32. For the implementation of [8], we set the threshold value T equal to 116 as suggested by the authors. The filter size for the used in [8] is set to 5×5.

In this work, we use 100 images of size 1600×1200 as our test images. These images present a wide variety of images, and with different characteristics. Examples of these images are shown in Fig. 1(a), Fig. 2(a), and Fig. 3(a). These images are free from impulse noise, and we denote them as e. Then, we contaminate these images with impulse noise to get the corrupted images, f. If image e is corrupted by Q% of noise, 0.5Q% will be the positive impulses and another 0.5Q% will be the negative impulses. We then process f using the four mentioned methods in this section. The results are presented in terms of the visual appearance, root mean square error (RMSE) and processing time.

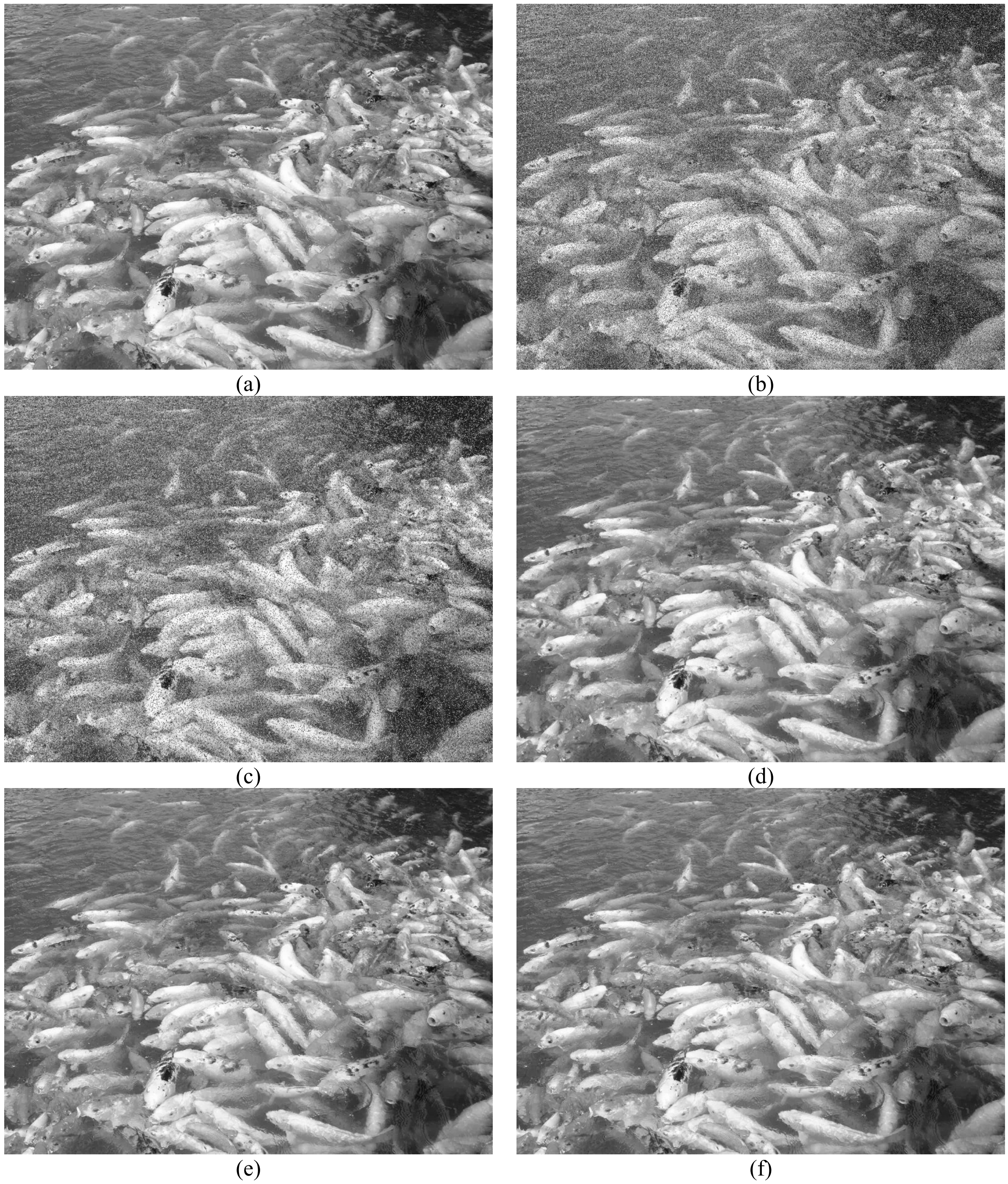

Fig. 1. "*Koi*" (a) The original image. (b) Image corrupted by 25% of impulse noise. (c) Result from the switching method proposed by Luo [7] (RMSE = 55.38, processing time = 327ms). (d) Result from the switching method proposed by Zhang and Karim [8] (RMSE = 8.16, processing time = 702ms). (d) Result from the adaptive method proposed by Hwang and Haddad [18] (RMSE = 4.89, processing time = 1217ms). (e) Result from our proposed method (RMSE = 4.25, processing time = 406ms).

RMSE value is used to evaluate the correction error of the method. We use the standard definition of RMSE value. This measure is defined by the following equation:

$$\mathrm{RMSE} = \sqrt{\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[g(x,y)-e(x,y)]^2} \qquad (9)$$

Fig. 1 shows the results when these four methods are applied to an image that is corrupted by 25% of impulse noise, which is considerably low level of noise. Based on visual inspection, all methods tested in this work, except method [7], successfully eliminate the impulse noise from the image. Our method produces the output with the lowest RMSE, and the processing is faster than the method proposed in [8] and [18].

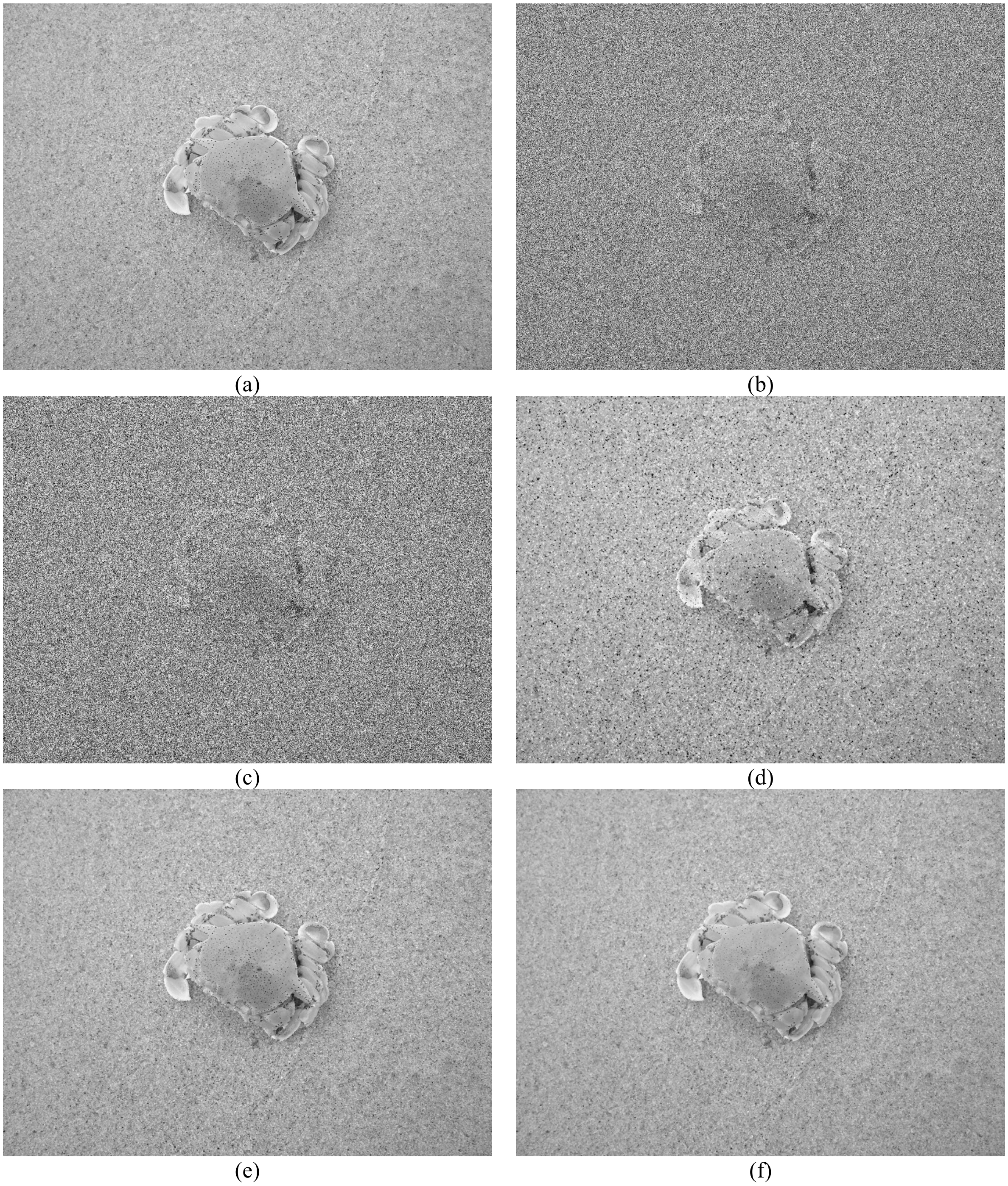

Fig. 2. "*Crab*" (a) The original image. (b) Image corrupted by 60% of impulse noise. (c) Result from the switching method proposed by Luo [7] (RMSE = 103.65, processing time = 873ms). (d) Result from the switching method proposed by Zhang and Karim [8] (RMSE = 38.44, processing time = 686ms). (d) Result from the adaptive method proposed by Hwang and Haddad [18] (RMSE = 16.08, processing time = 1529ms). (e) Result from our proposed method (RMSE = 14.65, processing time = 1216ms).

Fig. 2 shows the results when the methods are tested to the image with a moderate level of noise, which is 60% of impulse noise. The intensity range of the object in this image, which is the crab, occupies almost the same intensity range as its background, (i.e. the intensity of the sands). The object is mostly identified by its texture. The sand granules and the crab's skin are not presented by homogenous regions, but they are built up from high frequency components, where majority of the pixels have a considerably high contrast with its surrounding. This characteristic is similar to the characteristic of the impulse noise.

In Fig. 2, only method [18] and our method successfully clean up the image. Method [8] is only able to remove some of the noises. The results also show that, although visually our output is not as sharp as the output produced by [18], our method produces the smallest RMSE. The processing time is slightly lower than method [18].

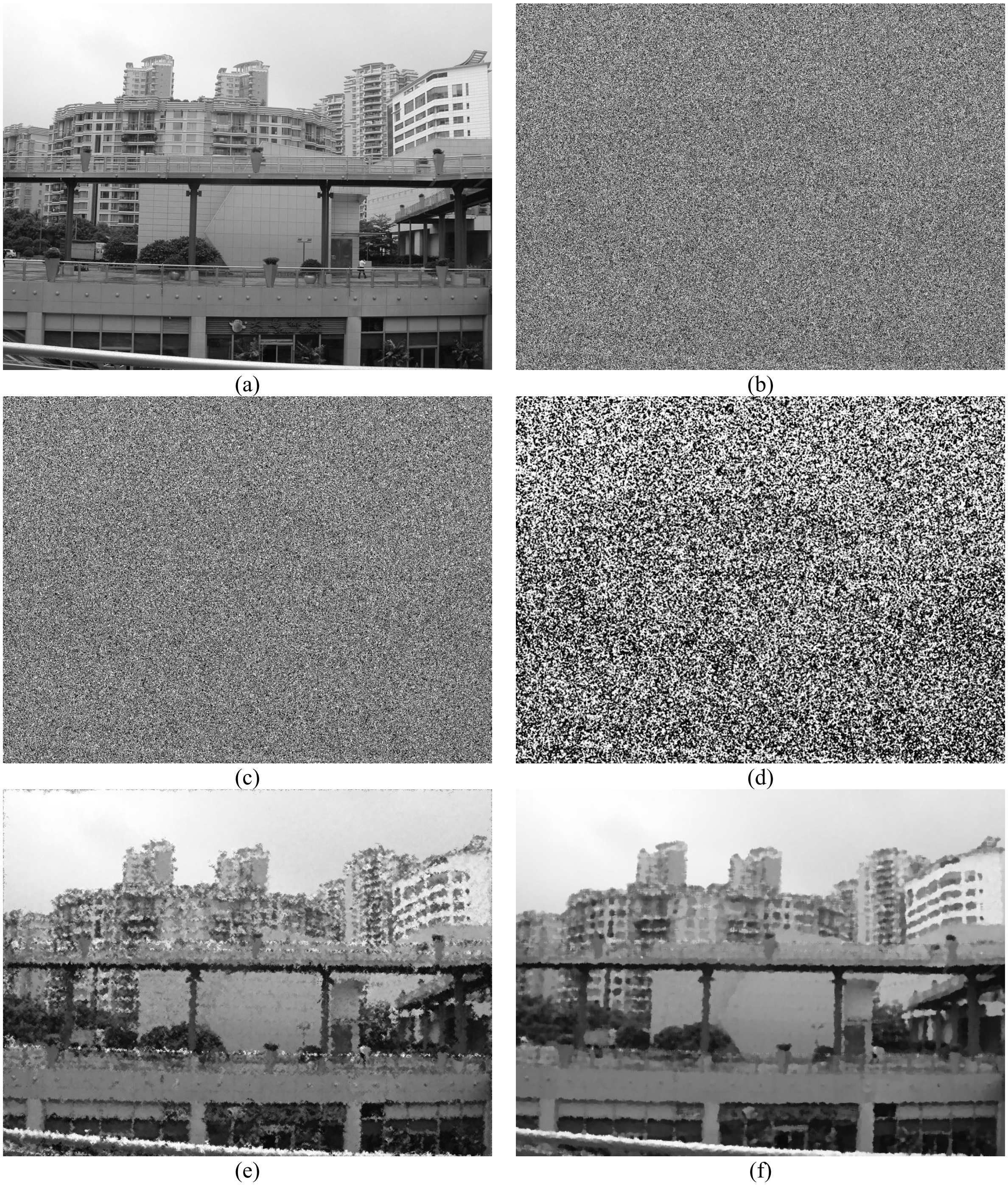

Fig. 3. "*Buildings*" (a) The original image. (b) Image corrupted by 95% of impulse noise. (c) Result from the switching method proposed by Luo [7] (RMSE = 142.99, processing time = 1139ms). (d) Result from the switching method proposed by Zhang and Karim [8] (RMSE = 132.25, processing time = 577ms). (d) Result from the adaptive method proposed by Hwang and Haddad [18] (RMSE = 34.51, processing time = 33931ms). (e) Result from our proposed method (RMSE = 25.00, processing time = 3027ms).

The results when the methods are tested to the image with a very high noise level, which is 95% of impulse noise, are shown in Fig. 3. There are many objects' edges and lines appear in the original image. Edges and lines are the main features to be preserved in many filter designs, including [8]. The high corrupted image is shown in Fig. 3(b). Visually, we cannot obtain any information from this image, due to the very high noise level. The corrupted image only appears as a combination of black and white dots.

Fig. 3 shows that although method [7] and [8] require short processing time, these two methods completely failed to recover the image from the high level of impulse noise. There are no information can be obtained from the corresponding images. Both method [18] and our method failed to preserve the fine lines, such as the lines of the tiles, in the image. However, these two methods produce outputs that can show a rough structure of the buildings clearly. It is visible that our method produces the output with less distortion. Furthermore, our method, similar to the case of low and moderate noise level, produces the lowest RMSE. Furthermore, the processing time needed by our method is only about one tenth from the time required by method [18].

Table I shows the average measures, based on 100 test images, taken at the noise level of 95%. Noise level of 95% is the highest noise level applied in this work. We show this table in order to see the worst performance of these methods. At this high percentage of noise, our proposed method requires slightly longer processing time, compared with method [7] and method [8]. But this is compensated with the surprisingly low RMSE value.

TABLE I
AVERAGE MEASURES TAKEN AT THE NOISE LEVEL OF 95%

Method	RMSE	Processing Time
Method [7]	137.73	1.12s
Method [8]	126.65	0.57s
Method [18]	26.37	22.47s
Our method	18.76	2.67s

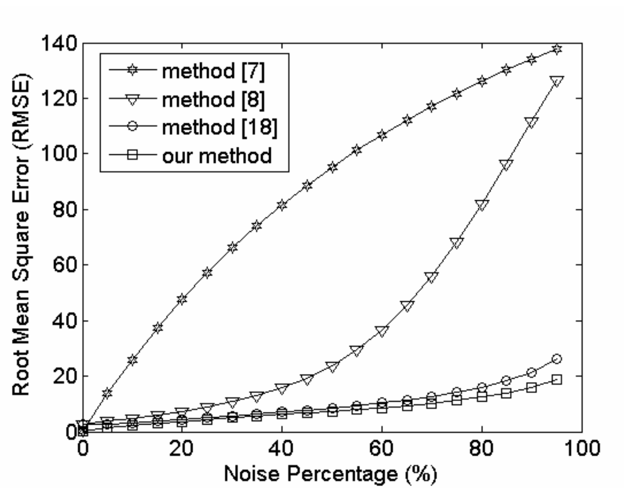

Fig. 4. The graph of the average RMSE value, calculated from 100 image samples, versus the noise level.

Fig. 4 shows the graph of the average of RMSE value calculated from 100 image samples versus the noise level. It is shown that our method produces the lowest RMSE value, regardless the noise level that corrupts the image. Method [18] is the second lowest, followed by method [8] and method [7]. Method [7] and method [8] have high value of RMSE mainly because of these methods failed to detect the noise pixel correctly. Our method and method [18] have low RMSE value mainly because these methods are adaptable to the local noise level. Bigger filter will be applied to the area with higher local noise density. However, method [18] has a slightly higher RMSE value compared to our method. This is because method [18] takes all pixels, including the "*noise pixels*" for the calculation of median value. Our method, on the other hand, only considers "*noise-free pixels*". Therefore, our method produces more accurate result.

Fig. 5 shows the graph of the average processing time calculated from 100 image samples versus the noise level. The graph shows that method [18] significantly has long processing time. The reason for this is because method [18] requires a long time to determine the correct filter size to be applied at each pixel location, which requires looping. For each loop, method [18] calculates the values of minimum, maximum, and median, which is relatively more complicated procedure compared with the other three methods. Method [7] and [8] require less processing time because these two methods use a constant small filter size. Method [7] uses 3×3 filter, and method [8] uses 5×5 filter. The processing time required by method [8] is almost constant, because the same procedure is applied to all pixels in the image, regardless the level of noise. The processing time for method [7] is increasing with the increase of the noise level. This is because as the noise level increased, there are more "*noise pixels*" need to be filtered.

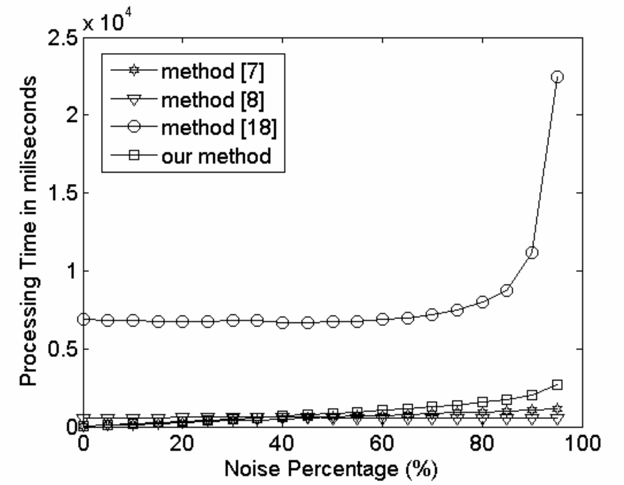

Fig. 5. The graph of the average processing time needed, calculated from 100 image samples, versus the noise level.

Similar to method [7], the processing time for our method is also increasing as the noise level increases. In addition to the increment in the number of the "*noise pixels*" that need to be processed, the processing time is also increased because bigger filters are being used. As shown by Fig. 5, for the noise level less than 60%, our method requires shorter processing time than method [8], which uses 5×5 filter. This is because, for our method, when the impulse noise is greater than or equal to 60%, the minimum filter size needed for the processing, according to (8), should be greater than 5×5 window.

I. CONCLUSION

This paper presents a novel technique to remove impulse noise from highly corrupted images. The method is actually a hybrid of the adaptive median filter with the switching median filter. One of the advantages of this method is that this method does not need the threshold parameter. Thus, no tuning or training is required. Furthermore, the filter size is adaptable to the local noise density. Experimental results show that this method always produces good output, even when tested with the high level of noise. The details inside the image are preserved and the RMSE value is small. This method is relatively a fast method and suitable to be implemented for consumer electronic products, such as digital camera. For the corrupted images with less than 55% of noise, the method requires only less than one second of processing time.

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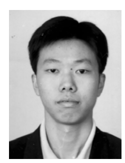

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