Switching Median Filter with Signal Dependent Thresholds Designed by using Genetic Algorithm

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Abstract: In this paper, we propose a new switching median filter with signal dependent thresholds designed by a genetic algorithm (GA). The switching median filter detects noise-corrupted pixels based on a threshold. Then it restores only the detected pixels. The present switching median filter deals with the random-valued impulse noises, whose distribution is ideally assumed as a uniform distribution. In the present method, the switching median filter, which has two kinds of the thresholds, is introduced. One is switching thresholds to detect the noise, and the other is selecting thresholds to choose the suitable switching threshold. As the suitable selecting threshold, a variance of signals is used. Then all of the switching and selecting thresholds of the proposed switching median filter are automatically optimized by using GA. To optimize the thresholds with GA, distribution distance between the assumed and the detected noises is employed as a fitness function. The validity and effectiveness of the proposed method is verified by some experiments.

1 INTRODUCTION

Along with developments of digital technologies, high quality digital images are strongly needed in many research and application fields. However, the digital images are often corrupted by the impulse noise in the image sensing and/or transmission processes. It is thus significant to restore the noise in the image before subsequent processing. In order to realize a fine restoration of the image corrupted by the salt-and-pepper impulse noise, various nonlinear filters based on the median filter have been studied so far (Chen et al., 1999), (Chen and Wu, 2001), (Akkoul et al., 2010). Especially a switching median filter, which was proposed by Sun and Neuvo (Sun and Neuvo, 1994), has frequently employed and studied in order to apply it to a random-valued impulse noise removal in recent years (Suetake, 2002), (Ng and Ma, 2006), (Zhang et al., 2008), (Suetake et al., 2011).

The typical switching median filters include a noise detector based on a switching threshold, and carry out the median filtering to only noise-corrupted pixels. In order to apply the switching median filter effectively, its switching threshold of the detector has to be appropriately tuned for the signal of concern. However, it is difficult to determine the optimal threshold automatically, because the suitable threshold varies depending on a mix of factors, e.g., a property of input image, noise content rate, the window size of the detector and so on.

To cope with this problem, the authors proposed a distribution distance-based threshold auto-tuning method for switching median filter so far (kubota and Suetake, 2010). In this method, the distribution distance between a noise model assumed beforehand and the noise signal detected by the detector was introduced as a distinct indicator for the optimal tuning of the threshold. This method can free the users from the tiresome tuning, and has been also applied to the random-valued impulse noise removal of the color image (kubota and Suetake, 2011). However, the switching median filter with only a fixed switching threshold has an inherent limitation on the noise detection performance.

To address this issue, we propose a new switch-

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ing median filter with some signal dependent thresholds and their optimal designing method based on the noise probability distribution. In this paper, the switching median filter, which has two kinds of the thresholds, is introduced. One is switching thresholds to detect the noise, and the other is selecting thresholds to choose the suitable switching threshold. In the proposed method, we employ a variance of signals for the selecting threshold. Thus, the suitable switching threshold is decided depending on the signal of concern by using the selecting thresholds.

All of the switching and selecting thresholds of the proposed switching median filter are automatically designed by using GA, which is a search algorithm based on the mechanism of natural selection and natural genetics (Goldberg, 1989), (Davis, 1990). GA solves optimization problems by using individuals which are represented by bit-strings or real valued-genes. In the proposed method, GA tunes all thresholds so as to minimize a distribution distance between the assumed and the detected noises.

Through the experiments, the effectiveness and validity of the proposed method are illustrated.

2 NOISE MODEL AND SWITCHING MEDIAN FILTER

2.1 Random-valued Impulse Noise

In this paper, we consider a monochrome image corrupted with the random-valued impulse noise in a transmission of the digitalized signal. Impulse noises are caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware or transmission in a noisy channel.

A signal $x(i,j)$ corrupted with the random-valued impulse noise is represented by:

$$x(i,j) = \begin{cases} s(i,j), & \text{probability} \quad 1-p, \\ h, & \text{probability} \quad p, \end{cases} \tag{1}$$

where, $s(i,j)$ is the source signal, and takes 256 level (8 bit) values. p represents a noise occurrence probability. The noise-corrupted pixel value h takes from 0 to 255, because each bit in $s(i,j)$ inverts randomly.

This model is the most popular and focuses on a bit error in the digitalized signal transmission. Therefore, the signals corrupted with the random-valued impulse noises can be assumed as a uniform distribution.

2.2 Detailed-preserving Median Based Filter

A detailed-preserving median based filter is the most popular switching median filter (Sun and Neuvo, 1994). In this method, the impulse noises are detected by considering difference between a pixel value of concern and a median of its neighboring pixel values.

This method uses a noise position image $f^{(\varepsilon)}(i,j)$ defined by:

$$f^{(\varepsilon)}(i,j) = \begin{cases} 1, & |x(i,j) - x_{\mathrm{MED}}(i,j)| \geq \varepsilon, \\ 0, & \text{otherwise}, \end{cases} \tag{2}$$

where $x_{\mathrm{MED}}(i,j)$ stands for the output signal at the pixel (i,j) by the ordinary median filter. The noise position image contains coordinate information of the detected noises. In the noise position image, "1" represents that the pixel is corrupted by the noise. The switching median filter carries out the median filtering only for the detected pixels by using the noise position image. Here ε is a threshold.

In the past, various types of the switching median filter have been proposed for the effective detection of the salt-pepper impulse noise. Furthermore, some of them have been also applied to the detection of the random-valued impulse noise. However, in the conventional methods, the suitable threshold ε has been adjusted manually and empirically depending on the situations, because effective indicators for the filter design have not been discussed so far. Additionally, the switching median filter with only a fixed threshold has an inherent limitation on the noise detection performance.

In order to raise the noise detection performance, it is preferable to change the threshold depending on the target and its neighboring signals automatically.

3 PROPOSED METHOD

3.1 Counstruction of Proposed Switching Median Filter

The proposed switching median filter has two sets of thresholds. One is the switching thresholds $\{\varepsilon_m \mid m = 1,\cdots,N\}$, and the other is the selecting thresholds $\{v_n \mid n = 1,\cdots,N-1\}$. Each switching threshold is a value, and it is used in order to judge the target signal as the source or the noise. The selecting thresholds work to choose the suitable switching threshold from the set of the switching thresholds. Thus, the proposed switching median filter is expressed by:

$$f^{(\varepsilon^o)}(i,j) = \begin{cases} 1, & |x(i,j) - x_{\mathrm{MED}}(i,j)| \geq \varepsilon^o, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

$$\varepsilon^o = \begin{cases} \varepsilon_1, & v < v_1, \\ \quad\vdots & \\ \varepsilon_m, & v_{n-1} \leq v < v_n, \\ \quad\vdots & \\ \varepsilon_N, & v_{N-1} \leq v, \end{cases} \tag{4}$$

where v_n is a variance value calculated from $x(i,j)$ and its neighboring signals in a window. Additionally, these thresholds satisfy the following conditions:

$$0 < \varepsilon_1 < \cdots < \varepsilon_m < \cdots < \varepsilon_N, \tag{5}$$

and

$$0 < v_1 < \cdots < v_n < \cdots < v_{N-1}. \tag{6}$$

3.2 Adaptive Threshold Tuning by Genetic Algorithm

In the proposed switching median filter, all of the thresholds, which are $\{\varepsilon_1, \cdots, \varepsilon_m, \cdots, \varepsilon_N\}$ and $\{v_1, \cdots, v_n, \cdots, v_{N-1}\}$, are decided by using GA.

In the proposed method with GA, an individual $\boldsymbol{I}_k$ is constructed by the serially-concatenated switching and selection thresholds. Thus the k-th individual is represented by $\boldsymbol{I}_k = \{\varepsilon_{k1}, \cdots, \varepsilon_{km}, \cdots, \varepsilon_{kN}, v_{k1}, \cdots, v_{kn}, \cdots, v_{kN-1}\}$, where $5 \leq \varepsilon_{km} \leq 100$ and $10 \leq v_{kn} \leq 7,000$.

In the optimization process of GA, crossover, mutation and selection operators are applied to the population. The proposed tuning method employs a distribution distance between a noise model assumed beforehand and the noise detected by the detector as a fitness function. The distribution distance is a good indicator for the evaluation of the noise detecting performance, and its validity for the single threshold adjusting has been verified in (kubota and Suetake, 2010). When the distribution distance is small, it is thus judged as a fine noise detection is achieved. The fitness function with its modification to the proposed switching median filter is described below.

The sets of the suitable thresholds $\{\varepsilon^*_m \mid m = 1, \cdots, N\}$ and $\{v^*_n \mid m = 1, \cdots, N-1\}$, which maximize the fitness function F, is searched. The fitness function F_k of k-th individual is represented by:

$$F_k = \frac{1}{1 + D(H_{d,(\Omega_k)}, H_a)}. \tag{7}$$

$D(H_{d,(\Omega_k)}, H_a)$ is the distribution distance (L_1 norm) and is represented by:

$$D(H_{d,(\Omega_k)}, H_a) = \sum_{\ell=0}^{255} |H_{d,(\Omega_k)}(\ell) - H_a(\ell)|, \tag{8}$$

where $H_{d,(\Omega_k)}$ stands for a probability density function of the noises detected with the set of the thresholds $\Omega_k = \{\varepsilon_{km}, v_{kn} \mid m = 1, \cdots, N, \text{ and } n = 1, \cdots, N-1\}$. The probability density function is then obtained from a normalized histogram of a set of $x(i,j)$ which satisfies $f^{(\varepsilon^o)}(i,j) = 1$. H_a represents the probability density function of an assumed random-valued impulse noise, i.e., a uniform distribution, because the assumption on the distribution of the noise is imposed by the model of Eq. (1). $H_a(\ell)$ is $\frac{1}{256}$ for arbitrary ℓ here, because H_a is a uniform distribution.

The proposed method has three features from the viewpoint of the usefulness, although the proposed method is very simple. One is that the proposed method can determine the suitable and specific thresholds for various input images and/or their noise occurrence probability automatically, if the noise corrupted to input image is the random-valued impulse noise. Another is that the proposed method can adjust some kinds of thresholds by evaluating only a distribution distance. The other is that the proposed method does not require desirable output images for the adjusting, because this method works only with the internally-assumed noise model and the filter outputs. Therefore, it can be said that the proposed method is very effective in the situation where the MSE evaluation cannot be performed. Furthermore, the proposed method can be used without any changes of algorithm even if the noise occurrence probability is changed.

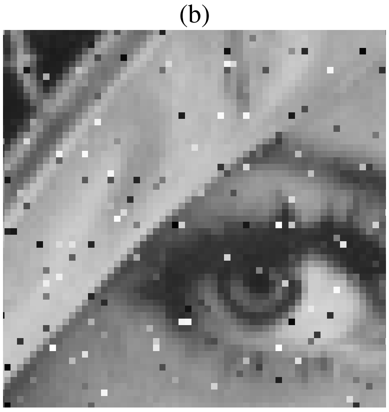
4 EXPERIMENTAL RESULTS

The effectiveness and validity of the proposed method are verified by experiments employing a digital image as shown in Figure 1. Figure 1 constitutes of 512×512 pixels. In the experiments, the input images are corrupted by the random-valued impulse noise with $p = 0.05$. The enlarged image of input image is shown in Figures 1(c).

In the experiment, we used the switching median filter with 3 switching thresholds and 2 selecting threshold, i.e., $N = 3$. The window size of the switching median filter is 3×3. The noise removal performance of the proposed method is compared with that of the ordinary switching median filter, which has only single switching threshold. Furthermore, the noise removal performance of the proposed tuning

(a)

(b)



(c)

Figure 1: Test image: (a) Original noise-free image, (b) Enlarged image of a part of (a), (c) Enlarged input image.

method is also compared to those of a mean square error (MSE)-based tuning method and L_1 norm-based method. In this experiment, MSE is used as an index for the quantitative evaluation, although the evaluation based on MSE can not be applied in the practical situation. The MSE is calculated from the original noise-free image shown in Figure 1(a) and the output image restored by the switching median filter. The MSE becomes small when the restored image is similar to the original one.

In the MSE-based method, each threshold of the switching median filter is decided so as to minimize the MSE between the original noise-free image and the output image obtained by the switching median filter. In the same manner, each threshold of the switching median filter by using the L_1 norm-based method is decided so as to minimize the L_1 norm between distribution distances of the internally-assumed noise and the noise detected by the switching median filter. To decide the thresholds based on the MSE and the L_1 norm and to reduce the computational costs, a spatial segmentation search is used. The step size and the lower and upper limits is each thresholds are shown in Table 1. From Table 1, we can estimate that the number of trials is 336,000 in order to obtain the best combination of all the thresholds. In this experiment, the computation time of 1 trial needs 0.142 second.

Table 1: Step size and range of each threshold.

Threshold	Step	Lower	Upper
ε_1	1	15	49
ε_2	1	50	79
ε_3	1	80	100
v_1	1,000	1,000	4,000
v_2	1,000	6,000	9,000

In the GA of the proposed method, the number of genes in each individual is 5 (3 switching and 2 selecting thresholds). The population size is 100. The range of each threshold is the same to that in Table 1. The window size for the calculation of the variance (selecting threshold) is 5×5. The crossover, mutation and selection methods are the BLX-α crossover (Eshleman and Schaffer, 1993), uniform mutation and roulette wheel selection with the elitism, respectively. Furthermore, the crossover and mutation probabilities are 0,3 and 0.05, respectively. The number of generations for the search is 1,000. Thus, the number of trials is 100,000 in order to finish the search in the proposed method, and less than those of the MSE and the L_1-based methods.

Table 2 shows the tuning results of the MSE, L_1 and the proposed method.

From Table 2, it is observed that the noise restoration performance is improved slightly when the number of the switching thresholds increases. Besides, L_1-based and the proposed methods seem to be good, although the obtained thresholds are not perfectly same to that by the MSE-based method. From these results, it is confirmed that the distribution distance between the assumed and the detected noise is a good indicator for the multiple thresholds tuning. Furthermore, the distribution distance-based threshold adjusting method seems to be highly promise a secure performance even if the detector has some thresholds.

Table 2: Experimental results by the MSE-, the L_1-based optimal tuning and the proposed tuning methods.

Method	ε_1^*	ε_2^*	ε_3^*	v_1^*	v_2^*	MSE	L_1
MSE-based method	27	-	-	-	-	9.0	0.16
L_1-based method	21	-	-	-	-	9.7	0.13
MSE-based method	25	50	80	2,000	6,000	8.7	0.15
L_1-based method	22	54	85	3,000	6,000	9.4	0.12
Proposed method	12	22	83	60	5,862	9.4	0.12

(a)

(b)

(c)

Figure 2: Noise restored images, (a) MSE-based method, (b) L_1-based method, (c) Proposed method.

Figure 2 shows the parts of output images restored by the switching median filtering with the signal dependent multiple thresholds obtained based on the MSE, L_1-based and the proposed methods. It is observed that the restoration images by the L_1-based and the proposed method are the almost same to those by the MSE-based optimal tuning. Furthermore, the proposed method seems to be effective in the situation where the MSE evaluation cannot be performed (i.e., the desirable filtered image cannot be obtained beforehand).

Figure 3(a) shows a transition of the smallest L_1 norm of the best individual in the searching process with the GA. From Figure 3(a), it can be observed that the better thresholds are found as the generations progresses by the proposed method. Additionally, Figure 3(b) shows the MSE calculated by the best individual at each generation. From Figure 3(b), it can be seen that the good thresholds which is almost the best solution has been found arround 50-th generation. Thus, the number of trials in order to obtain the good thresholds in the proposed method is 5,000, which is calculated by the number of generation and the population size. On the other hand, the number of trials of the spatial segmentation search is 336,000 in order to obtain the best combination of all the thresholds. Therefore, the proposed method can find the appropriate and reasonable thresholds faster than the $L-1$-based spatial segmentation search.

From these results, the effectiveness and validity of the proposed method are confirmed.

5 CONCLUSION

In this paper, we proposed a new switching median filter with signal dependent thresholds and their optimal designing method by using GA.

The thresholds of the proposed switching median filter are automatically optimized by using GA. To optimize the thresholds with GA, the distribution distance between the assumed and the detected noises is used as the fitness function. The effectiveness and validity of the proposed method were illustrated.

Future works are to improve the searching perfor-

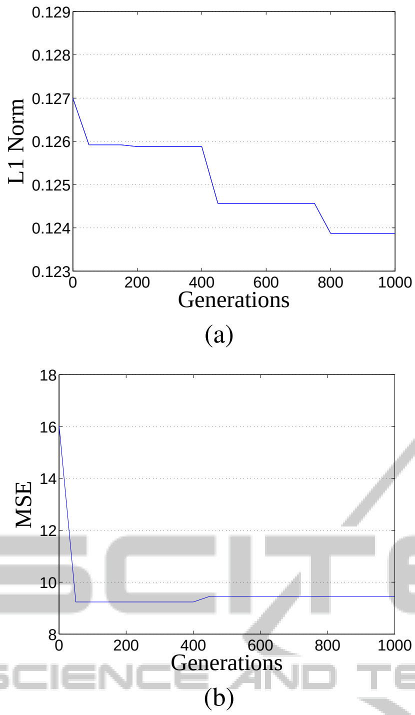


Figure 3: Optimizing transitions of L_1 norm by the proposed method, (a) L_1 norm of the best individual, (b) MSE calculated by the best individual.

mance of GA and to establish other noise models for various types of the noises.

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