Evolutionary Image Enhancement for Impulsive Noise Reduction

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Abstract. Image enhancement with various image filters might be better than that with a single filter, but it is very difficult to find a set of appropriate filters. In this paper, we propose a novel method that uses the genetic algorithm to find a filter set for reducing impulsive noises in images. The proposed method has been verified with benchmark images in image enhancement. Moreover, it does not require any expert knowledge to find the type and order of filters for a given domain, so it can be easily applied to other applications of image processing.

1 Introduction

In general non-linear signal processing aims to detect objects on images, but it is often hard to correctly extract features when the quality of images is low. Filtering that reduces image noises and smoothing that removes some forms of misfocus and motion blur are representative image filtering techniques. Histogram-based, mask-based and morphology-based image filters are popular for the enhancement [1].

Impulsive noises are known as salt-and-pepper noises, where the noisy pixels take only the maximum (salt) or the minimum (pepper) values in the dynamic range. Conventional median filters are the most popular non-linear filter to remove impulse noises, but many filters require a complex formulation for better performance [2]. To reduce noises, the usage of various filters together might be effective rather than that of only a single filter, but it requires the expert knowledge to compose a filter set.

Since it is actually impossible to examine all possible combinations of filters, it requires a heuristic algorithm. The genetic algorithm is a representative evolutionary algorithm, which is based on the mechanisms of natural selection and the survival of fittest. It has been successfully applied to many problems such as searching and optimization [3]. In this paper, we adopt the genetic algorithm to find out a set of proper filters for noise reduction in images.

2 Related Works

For impulsive noise reduction, the median filter is the most popular non-linear filter because of its good de-noising power and computational efficiency [2]. The

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topological median filter [4] is recently introduced as a median filter, and it uses the fuzzy concepts for the extraction of edges in noisy images.

Since impulsive noises are special in which a pixel has only maximum and minimum, the decision-based strategies [5] were proposed. They first identified possible noisy pixels and then replaced them by using the filter, leaving all other pixels unchanged. Especially, they work well for the impulsive noises of high level, but it is limited in detecting noises.

Harvey *et al.* used the genetic algorithm to determine the sequence and structuring element of morphological filters [6], which requires many genes to represent the filter. For image enhancement like impulsive noise reduction, several studies have proposed new filters showing good performance. For combining not only simple filters but also these various filters of good performance, the appropriate method having scalability is required.

3 Noise Reduction Based on the Genetic Algorithm

In order to improve the quality of images, noises should be eliminated by using an appropriate image filter. When there are m filters available, the number of possible ordered subsets of n filters is given by m^n. Trying all cases to find out the best one is practically impossible when there are lots of filters available. In this paper, the genetic algorithm is used to search a filter set, in which the proper type and order of filters are determined.

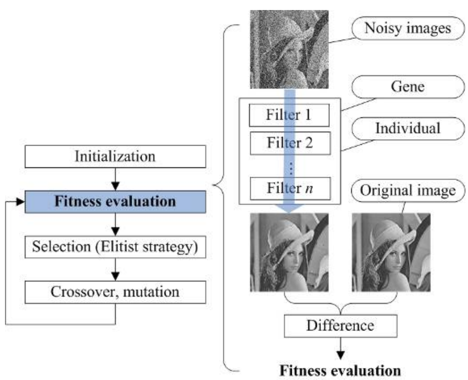

Fig. 1. The process of evaluating the fitness (fitness function)

Fig. 1 shows the procedure of the proposed method which also presents the process of evaluating the fitness. In each generation, the fitness of candidate solutions as individuals is evaluated by the fitness function, and individuals with higher fitness are stochastically selected and applied with genetic operators such as crossover and mutation to reproduce the population of the next generation. Elitist-strategy that keeps the best individual of previous generation is used in the process of selection. Genes which compose an individual are represented as numbers representing the

Table 1. The description of image filters used in this paper

Group	Filter	Number
Histogram	Brightness (3 values), Contrast (3 values), Stretch, Equalize, Logarithm	1~9
Mask	Blur (6 masks), Sharper (4 masks), Median (10 masks)	10~29
Morphology	Erosion, Dilation, Opening, Closing (10 masks)	30~69
	None	0

corresponding filter. Training images including artificial noises are passed through filters of genes, and the fitness is calculated by the difference between the result image and the original image. Table 1 shows the type of 70 image filters used in this paper.

In order to measure the performance of a combination filter in noise reduction, the difference between the filtered image and the original image calculated by using the mean absolute error (MAE) and the peak signal-to-noise ratio (PSNR) [5]. The fitness function of the genetic algorithm is estimated by the equation (1) using the mean absolute error, where an individual that shows good enhancement performance obtains a higher score. Let $MAE_{\max}$ be the maximum MAE for an image, and $MAE_{\max}$ would be 255 for 8-bit grayscale images.

$$f(x) = 1 - \frac{MAE(x)}{MAE_{\max}} \tag{1}$$

4 Experiments

In the experiments, LENA and FRUIT are used as the benchmark images. Each image is 256×256 and 512×512 for 8-bit grayscale images. The noisy images will be corrupted by salt (value 255) and pepper (value 0) noises with predefined probability. The noise levels varied from 10% to 70% with increments of 20%. The training images are 4 images as LENA with each noise level, and the test images are 8 images as LENA and FRUIT with each noise level. Table 2 shows the MAE and PSNR of training and test images compared to the original images.

Table 2. The analysis of training and test set

Set	Training				Test							
Image	LENA				LENA				FRUIT			
Noise level (%)	10	30	50	70	10	30	50	70	10	30	50	70
MAE	12.7	38.1	63.6	89.2	12.7	38.1	63.7	89.3	12.7	38.3	63.7	89.3
PSNR	15.5	10.8	8.57	7.10	15.5	10.8	8.5	7.09	15.4	10.6	8.44	6.96

Four filters are obtained for each training image, where there are 4 training images by the noise level. In addition, one filter is evolved for reducing all noises using the fitness as average mean absolute error of 4 images after filtering. Initial values of parameters in the experiments is as follows: 1000 generations, 30 populations, 5 gene

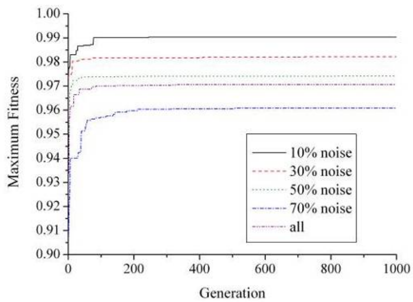

Fig. 2. The maximum fitness in each generation

Table 3. Type of other filters

Filter	Filter type				
Filter I	Median Diamond 3×3				
Filter II	Median Diamond 5×5				
Filter III	Median Rectangle 5×5				
Case I	Median 1×3	Median Diamond 3×3	NULL	NULL	NULL
Case II	Median Diamond 3×3	Median 1×3	Closing 1×3	Opening 1×3	Median 3×1
Case III	Median Diamond 5×5	Median Diamond 5×5	Median X 3×3	Median 1×3	Opening 1×3
Case IV	Median Rectangle 3×3	Median X 5×5	Median Rectangle 3×3	Opening Rectangle 5×5	Closing Rectangle 5×5
Case V	Median Diamond 5×5	Median X 5×5	Median X 5×5	Median 1×3	Median Diamond 5×5

length, 1 selection rate, 0.7 crossover rate, and 0.05 mutation rate. Fig. 2 shows the change of the maximum fitness in each generation, in which filters with the best performance are found before the 300th generation.

Table 3 shows the image filter of good performance and the filters evolved. The mean absolute error over all image filters was investigated on the training images, and 3 good filters which named filter I~III were obtained for comparing with the filters evolved. The filters which named case I~IV were the results of the evolution for each noisy image, and the filters which named case V were the result of the evolution for all images. Most of them included median filters, since the median filter was suitable for impulsive noise reduction. However, other filters such as opening and closing were also included for better performance.

Fig. 3 shows the comparative performance of the proposed method against other filters. The mean absolute error (MAE) is indicated by logarithm of 2 on y-axis. Total on x-axis indicates the sum MAE and the average PSNR of all images. Case I~IV in each environment performs the best against other filters in the criteria on the MAE and the PSNR. Fig. 4 shows examples of various filters by LENA with 30% noise and FRUIT with 70% noise. Case II and IV are better at reducing noisy pixels than a single filter.

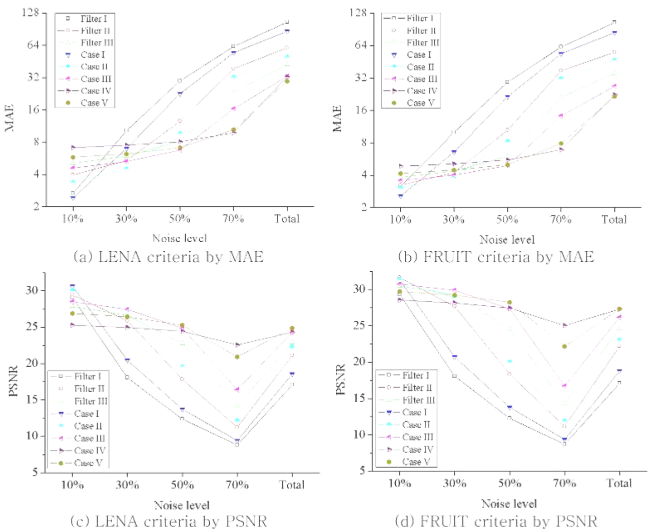

Fig. 3. The performance comparison with other filters

Fig. 4. Examples of various filters: (a)~(d) LENA, (e)~(h) FRUIT

Most filters performed well enough in only one environment, not in every environment. For example, case I and filter I worked well at 10% noise level, but not at 70% noise level. Case IV is also better than the other filters for 70% noise level, but it is worse than the other filters for 10% noise level. Case V does not show the best performance in any environment, but there is a little difference of performance compared to the best filter. Since there are many impulsive noise detectors and the noise level is also estimated by detector [5], case I~IV are applied in proper environment. If it is hard to estimate the noise level, case V can be preferred.

5 Conclusion

Even though the median filter is popular for impulsive noise reduction, there are many studies investigated to improve the image enhancement performance but they need some complex formula or the expert knowledge. In this paper, the combination of well-known and simple filters is determined by the genetic algorithm for impulsive noise reduction. In the experiments, for real images such as LENA and FRUIT, the filter obtained showed better performance than the other filters on the mean absolute error and the peak signal-to-noise ratio.

For the future work, we would like to apply the proposed method to the other image databases. By changing the fitness function of the genetic algorithm, the method for the better performance of object detection will be also studied. Since the proposed method does not need any expert knowledge, we can also apply the method to various applications for image processing.

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