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A Novel Extreme Learning Machine based Denoising Algorithm

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Abstract

We introduce a fast and effective algorithm extreme learning machine (ELM) and apply it to image denoising. GA-ELM algorithm we proposed uses genetic algorithm(GA) to decide weights and bias in the ELM. It has better global optimal characteristics than traditional optimal ELM algorithm. In this paper, we used GA-ELM to do image denosing researching work. Firstly, this paper uses training samples to train GA-ELM as the noise detector. Then, we utilize the well-trained GA-ELM to recognize noise pixels in target image. And at last, an adaptive weighted average algorithm is used to recover noise pixels recognized by GA-ELM. Experiment data shows that this algorithm has better performance than other denosing algorithm.

Keywords: *image denoising; extreme learning machine; genetic algorithm; rank-ordered logarithmic difference*

1. Introduction

During acquisition and transmission, digital images are often corrupted by additive noise that can be modeled as impulse noise most of the time. The main aim of an image denoising algorithm is then to reduce the noise level, while preserving the image features and details. Therefore, the purpose of this research is removing the impulse noise from image and reducing the loss of the features and details. There are many traditional denoising algorithms to impulse noise. The nonlinear methods have advantages, reveal more satisfactory consequence to a center extent and have better performance to preserve image features and details. The basic nonlinear denoising algorthms is the standard median (SM) filter [1]. It replaces each pixel in the image by the median value of the corresponding neighborhood window centered at this pixel. The SM filter works effectively for low noise densities but at the cost of blurring the image. One solution to this problem is the weighted median (WM) filter [2] which gives more weight to some values within the window than others. It emphasizes or deemphasizes specific samples, because in most applications, not all samples are equally important. The special case of the WM filter is the centre weighted median (CWM) [3] filter which gives more weight only to the centre value of the window. However, these filters do not perform well at higher noise densities. Besides, the filtered image is blurred with poor preservation of the image details. Each pixel of the image is considered to be noisy which may not be in practice. These filters do not detect whether a pixel in the image is actually corrupted by impulse or not and simply replace each pixel by the median value. A better tactic to avoid this drawback is to incorporate some decision making or switching action in the filtering. Firstly, it finds out whether each pixel is contaminated or not. Then, recovery method is applied on the pixel only if it is corrupted by noise. Corrupted pixels are replaced by the median values, while the noise-free pixels are left unaltered. Since not every pixel is filtered, undue distortion can be avoided as far as possible.

In recent years, there been having many researchers try to combine GA with Artificial Neural Networks (ANNs), to find an effective solution to complex problem and have a

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better understanding to the relations between learning and evolution, which become an active topic in the field of artificial life [3-11].

This paper proposes making use of gene algorithm to improve intelligent networks to find the most suitable network connection weights and network, then form a GA-ELM model and apply it to image denosing. The experiment points out that it gains good performance in image denosing.

2. Related Work

2.1. Noise Model

The classical salt and pepper noise is added to the value interval in $[0,255] \cup [255-\delta,255]$, where δ is 0 or a small positive integer. The model for images with noise is described as follows [12]:

$$I_{i,j} = \begin{cases} u_{i,j} & p \\ I_{i,j}^{0} & 1-p \end{cases} \qquad (1)$$

where $I_{i,j}$ is the image with noise, $I_{i,j}^{0}$ is the original part of $I_{i,j}$, $u_{i,j}$ is the noise part of $I_{i,j}$ (with usual value of 0 or 255), and p is the noise density.

2.2. Noise Model

In the literatures [13], Dong et al. proposed a new local image statistic ROLD which is based on ROAD feature [14]. It can identify more noisy pixels with less false hits and can be well applied to deal with random-valued impulse noise. Simulation results show that it outperforms a number of existing methods both visually and quantitatively. Based on this report, we adopt it in our algorithm. Its definition is shown as follows.

(1) Map the gray value of image $I_{i,j}$ to a value of $[0,1]$ by linear transformation, that is, $u(m) \in [0,1]$. This is the gray value of the pixel in image u at position m. The image has a window with its center on pixel $u(m)$, and its size is v $(2d+1)\times(2d+1)$; pixel $u(n)$ is one pixel in the window. The distance between the two pixels u and m is defined as

$$D_{m,n} = 1 + \frac{\max\left\{\log_a |u(m)-u(n)|, -b\right\}}{b}, n \in N_m^0(d) \qquad (2)$$

where $a,b>0$. The best distinction is achieved when $a=2$ and $b=5$.

(2) Sort all $D_{m,n}$,in a window in a descending order. If noise density $p>25\%$, then ROLD is the sum of the biggest 12 values sorted under a $5*5$ window size. Otherwise, it is the sum of the biggest 4 values that are sorted under a $3*3$ window size. For a variation between the noise pixel and its adjacent pixel in the window, the ROLD value will be a high integer. Based on this value, the ROLD of a normal pixel should be smaller for the consistency between itself and its adjacent pixel. Therefore, ROLD serves as an important definition of pixels and distinguishes between noise pixels and normal pixels.

3. Our work

3.1. GA-ELM

Huang and Zhu[15] proposed a simple learning method for SLFNs called Extreme Learning Machine (ELM) can be summarized as follows:

Algorithm ELM: Given a training set $\aleph=\left\{\left(\mathrm{x}_{i,}\mathrm{t}_{i}\right)\middle|\mathrm{x}_{i}\in\mathrm{R}^{n},\mathrm{t}_{i}\in\mathrm{R}^{m},i=1,\ldots,N\right\}$, activation function $g(x)$, and hidden node number $\tilde{N}$,

Step 1: Randomly assign input weight w_{i} and bias $b_{i},i=1,\ldots,\tilde{N}$.

Step 2: Calculate the hidden layer output matrix H .

Step 3: Calculate the output weight β

$$\hat{\beta}=\mathrm{H}^{\dagger}\mathrm{T} \qquad (3)$$

Where $\mathrm{T}=\left[\mathrm{t}_{1},\ldots\mathrm{t}_{N}\right]^{\mathrm{T}}$.

GA-ELM algorithm uses genetic algorithm (GA) to decide weights in the Extreme learning Machine algorithm. It has better global optimal characteristics than standard ELM algorithm. The details of the GA-ELM algorithm as follow:

Step 1: Organize the w_{i} and bias $b_{i},i=1,\ldots,\tilde{N}$ in the Net together by sequence order, and construct the initial population randomly;

Step 2: Use the Moore-Penrose generalized inverse analysis to calculate the output matrix H_{i}, obtained the weight w_{oi} of the output layer, and take Root-Mean-Square error (RMSE) of this generation population as its adaptive value $val(i)$. Then weight W and adaptive $val(i)$ output together;

Step 3: With crossover and mutation, generate the new one generation θ_{i+1};

Step 4: Circularly execute step 2 and step 3 until obtain the ideal optimal threshold difference or reach the maximum optimal number $\mathrm{N}\max$;

Step 5: After finding the optimal θ_{iop}, determine the current optimum c_{iop}, and then use the Moore-Penrose generalized inverse analytic method to obtain the output matrix H_{iop};

Step 6: Calculate the weights W_{oiop} of output layer ,and use the optimal c_{iop}、 σ_{iop}、 W_{oiop} et al parameters as configuration to setup the Net;

Step 7: Terminate the algorithm.

3.2. Denoising Algorithm

Noise pixels should be replaced by estimating the original value, and better noise filtering is generally achieved when the estimated value is closer to the original value. In this paper, we used an adaptive weighted average algorithm which varies for windows size and distance. This algorithm works as follows.

(1) Set a filter window W_f where the size is $W_s\times W_s$ is an odd value with a value of ≥ 3); its original size is $3*3$, and its center is on the pixel of the image. If the central point is not a noise point, shift the window W_f to make its central point be the next pixel of the image. Go to Step (2) when the central point is a noise point.

(2) Calculate the sum M of unpolluted pixels in W_f . If $M>9$ or $M>\frac{(W_s\times W_s+1)}{2}$, go to Step (4). If not, go to Step (3).

(3) Resize W_f , $W_s=W_s+2$, and go back to Step (2).

(4) Using M unpolluted pixels, calculate the output $L_{(i+s,j+t)}$ using formula (4), and replace the noise pixel. Consider the following:

$$L_{(i+s,j+t)} = \frac{\sum_{n=1}^{M} W_p(s,t) I_{(i,j)}^0 (i+s, j+t)}{\sum_{n=1}^{M} W_p(s,t)} \quad (4)$$

where $I_{(i,j)}^0(i+s, j+t)$ represents an unpolluted pixel value, with position $(i+s, j+t)$ and window center on (i, j). $W_p(s,t)$ is the weight; a pixel is more important if it is closer to the noise point. Therefore,

$$W_p(s,t) = \frac{1}{|s|+|t|} \quad (5)$$

3.3. Workflow

According to the function, the proposed algorithm can be divided into 3 steps shown in Figure 1:

Step 1: Detector training.

In this step, we added the noises known which have several characteristic: pixel's value, pixel's median in $3*3$ window size, pixel's ROLD, Pixel's position. We used value, median and ROLD as input, and use position as output, intending to train a GA-ELM as a detector.

Step 2: Noise detection.

After step 1, we get a well-trained detector which is capable of noise pixels position detection. In Figure 1(c), we can see from the process how noise pixels are detected. We enter the noised image itself (target image), pixel's median in $3*3$ window size, and pixel's ROLD into the detector mentioned above; then, we can estimate noised pixels position in target image.

Step 3: Image denoising.

In the last step, we used an adaptive weighted average algorithm which varies for windows size and distance to recover noise pixels which are recognized by GA-ELM to remove the noise from the image.

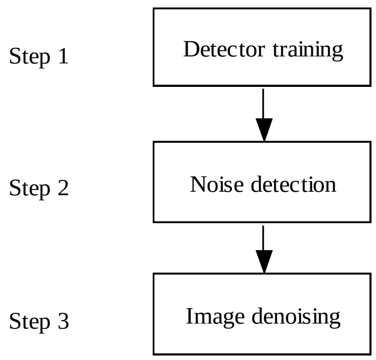


Figure 1. Workflow

4. Experiment

The qualitative assessment of the recovered image is done by forming a different (between the original and the recovered) image. For quantitative assessment of the restoration quality, the commonly used peak signal-to-noise ratio (PSNR) was used.

$$\text{PSNR}=20\log_{10}\left(\frac{255}{\sqrt{\frac{\sum\sum\left(x_{ik}-o_{ik}\right)^2}{Nm}}}\right) \tag{6}$$

where m is the total number of color components, N is the total number of image pixels, and x_{ik} and o_{ik} are the kth component of the noisy image pixel channel and its original value at pixel position 'i', respectively. Therefore, we use PSNR to evaluate the consequence of experiment in this paper.

Experiment 1.

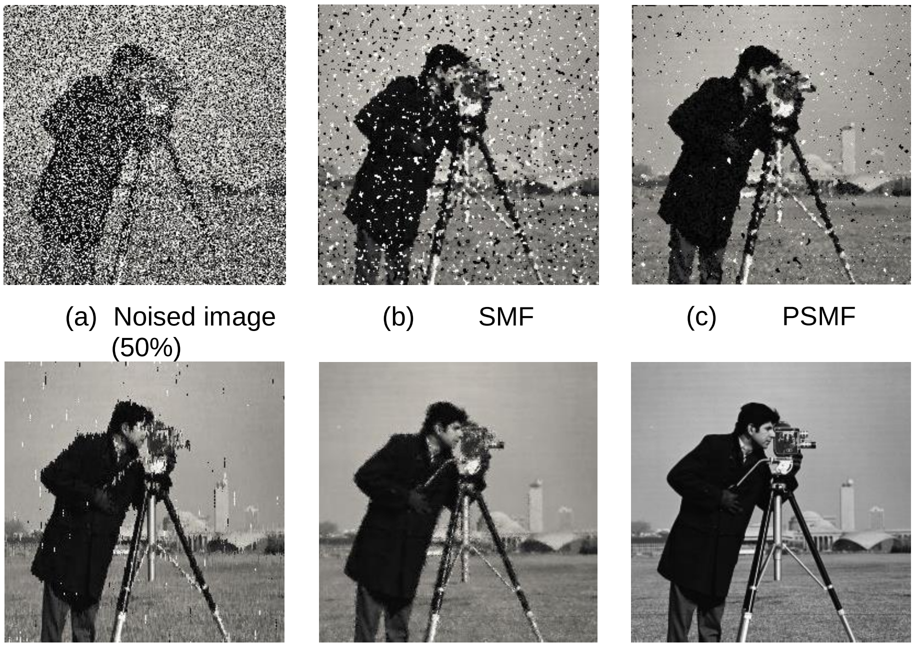
Add noise of 5%, 10%, 30% and 50% densities to classical images 'cameraman' and medical image 'heart'. Use standard median filter (SMF), progressive switching median filter (PSMF), and adaptive median filter (AMF), including the proposed algorithm, to remove noise from these noised images. Then, calculate their PSNR values, and data are shown in Table 1. It is clear that, for every image, the PSNR value of the proposed algorithm is higher than those of other methods; indicating the universality of the proposed algorithm's excellent performance. In removing noise and preserving details, our algorithm showed a robust performance, which became more obvious under a higher noise density.

Table 1. PSNR of Different Algorithm when the Image is Corrupted by Different Noise Density

Noised image	SMF	PSMF	AMF	Proposed
Cameraman				
5%	26.53	27.69	30.43	37.55
10%	26.01	27.28	28.49	34.91
30%	20.65	23.03	25.31	29.16
50%	14.19	18.56	19.07	25.67
heart				
5%	29.82	33.82	33.39	36.62
10%	29.63	33.10	30.42	34.90
30%	23.45	27.38	29.62	29.75
50%	14.27	21.67	25.92	28.82

Experiment 2.

Add 50% noise density to 'cameraman'. Use several algorithms, including the proposed algorithm, to filter these noised images, and show them in Figure 1. Compare the results subjectively; Figures 1(b), 1(c), and 1(d) are blurred seriously. In contrast, our method performs better and can suppress the noise successfully while preserving more details. It is obvious that Figure 1(e) has amazing performance in recovery compared to other traditional algorithms. This points out that our algorithm has better performance than other traditional algorithms when the normal image is highly corrupted.



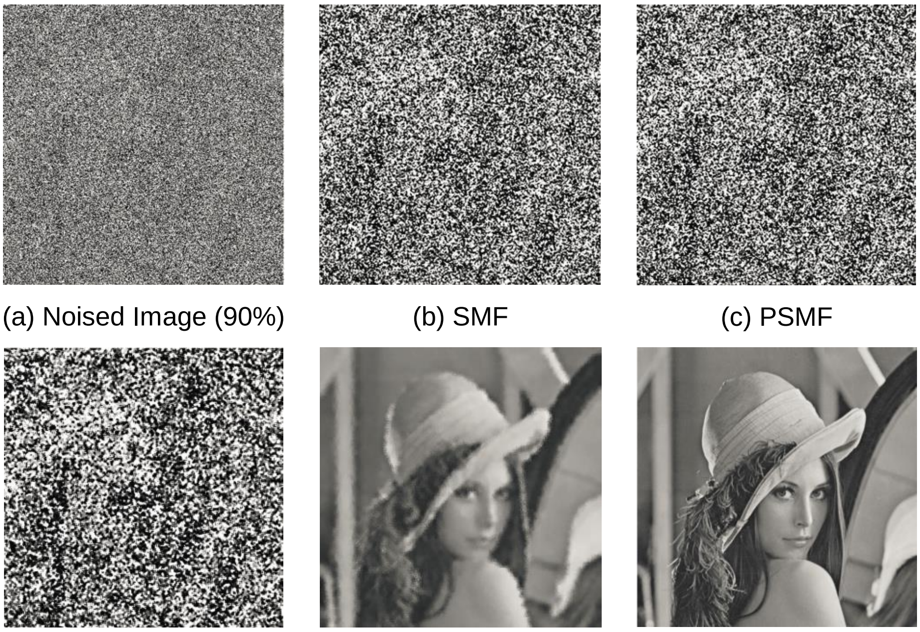
(a) Noised image (50%) (b) SMF (c) PSMF

(d) AMF (e) Our algorithm (f) Original image

Figure 2. 'Cameraman' with 50% Noise Density

Experiment 3.

Add 90% noise density to "lena." Use several algorithms, including the proposed algorithm, to filter these noised images, and show them in Figure 4. Compare the results subjectively; Figures 4(b), 4(c), and 4(d) are blurred seriously. In contrast, our method performs better and can suppress the noise successfully while preserving more details. It is obvious that Figure 4(e) has amazing performance in recovery compared to other traditional algorithms. This points out that our algorithm has better performance than other traditional algorithms when the normal image is highly corrupted.



(a) Noised Image (90%) (b) SMF (c) PSMF

(d) AMF (e) Our algorithm (f) Original image

Figure 3. 'Lena' with 90% Noise Density

5. Conclusions

This paper proposes a new denoising algorithm which uses GA-ELM as noise detector and ROLD feature as input. According to the result of experiment, compared with some other traditional image denoising methods, the algorithm this paper proposed performed effectively in aspects of noise removal and detail preservation, and its merit will be more obvious under higher noise densities.

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