Image Denoising based on Back Propagation Neural Network and Wavelet Decomposition

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Abstract

In this paper, an image denoising method based on back propagation neural network and wavelet decomposition is proposed. The wavelet decomposition coefficient of the image with noise is used as the training sample input, and the high frequency coefficient of the original image is used as the expected output to train the BP network. The obtained network can remove the noise in the image better. The experimental results are compared with the results of denoising using mean filtering, median filtering and Wiener filtering. The comparison results also show that the proposed method has some merits such as eliminating the noise of point and line regions.

Keywords

Back-Propagation Neural Network; Image Denoising; Wavelet Decomposition.

1. Introduction

The so-called noise, is obstructing the human visual organ or system sensor to receive the image information for understanding or analysis of various factors. General noise is an unpredictable random signal, and it can only be used to understand the probability of statistics. The noise of digital image mainly comes from image acquisition (digital process) and transmission process. The operation of the image sensor is affected by various factors such as the environmental conditions in the image acquisition and the quality of the sensing device itself. The image is subject to noise pollution during transmission mainly due to the interference of the transmission channel used. Because noise affects the whole process of image input, acquisition, processing and output, especially image input, the noise in acquisition inevitably affects the process and the final result. Therefore, the suppression of noise has become a very important step in image processing.

According to the noise source, it can be divided into three categories. First, it is recorded in the photographic film on the image by the impact of photosensitive particles noise; Second, it is procedued by the process of the optical image to the electronic form; Finally, the signal processing electronic amplifier will introduce thermal noise. Of the three noise sources, two are signal-related. For general image denoising, this dependency on the signal can be ignored. That is, it can be considered that the signal and the noise are independent of each other. The influence of noise on image can be divided into additive noise and multiplicative noise. Only additive noise is considered in this paper. Set $f(x,y)$ as the ideal image , $n(x,y)$ as noise, the actual output image is $g(x,y)$. For additive noise, its characteristics $n(x,y)$ are independent of the image intensity, that is $g(x,y)=f(x,y)+n(x,y)$.

In this paper, we use the back propagation algorithm in neural network to denoise the image based on wavelet analysis, and then use the wavelet decomposition coefficient of the original image and the image with noise to train the neural network, and get the better denoising network .

2. Wavelet analysis and Neural Networks

2.1 Wavelet analysis

Wavelet analysis is a kind of time-frequency analysis, which can express the signal's energy and intensity in time and frequency. It can analyze, process and extract the characteristic information contained in the signal, and get the time-frequency distribution characteristic with the expected information signal[1,2].

The schematic diagram of wavelet analysis is shown in Figure 1. The first layer decomposes to get a low-frequency components and three high-frequency components, which correspond to the horizontal direction, the vertical direction and the diagonal direction, respectively. The second layer decomposition is the decomposition of the first layer of low-frequency components and then a wavelet decomposition, the second layer of low-frequency components and three high-frequency components, analogy layer by layer. Then the n layers decomposition can get a wavelet low frequency coefficient and $3n$ high frequency coefficients.

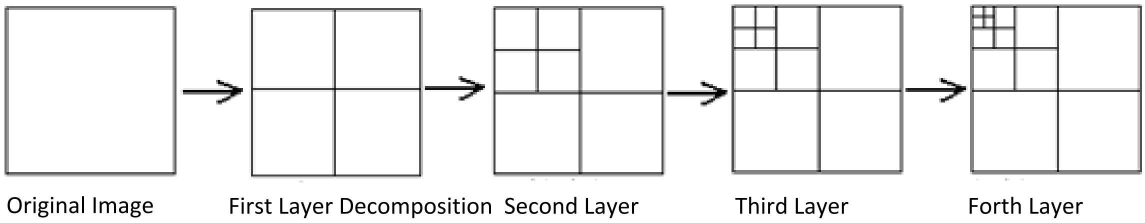


Figure 1. Schematic diagram of wavelet analysis

The low-frequency coefficients are the approximate components of the image, and the high-frequency coefficients contain the detail information of the image, which is the focus of people's attention and therefore the focus of image processing.

2.2 Back Propagation(BP) Neural Networks

BP neural network is a multi-layer feedforward neural network, due to the use of backward propagation learning algorithm, hence the name[3,4,5]. Figure 2 is the BP network learning process. BP network consists of three levels: input layer, hidden layer and output layer. There are fully connected between the upper and lower , and no connection between each layer.

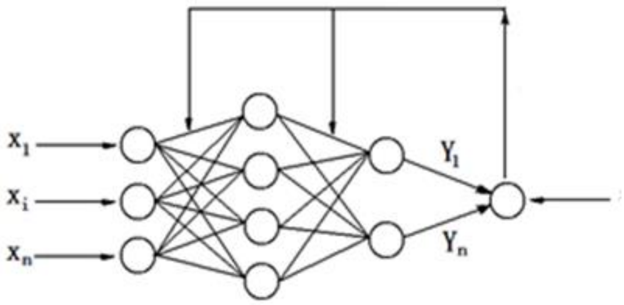


Figure 2. BP network learning process

When a pair of learning samples is provided to the network, the activation values of the neurons propagate from the input layer through the middle layer to the output layer, and the output responses of the neurons are obtained. The output signal is compared with the desired output signal. If the difference is within the range of the preset threshold, the next sample will be learned. Otherwise, the difference will propagate forward from the output layer, and the weights of the network will be adjusted by the error. The correction can make the actual output closer to the desired output. After learning all the samples, the neural network can be trained to complete the can be used.

A trained BP network can give appropriate results based on inputs, even if the input has not been trained. This feature makes the BP network very suitable for the use of input / target pairs of training, and does not need to have all the possible input / target pairs are trained.

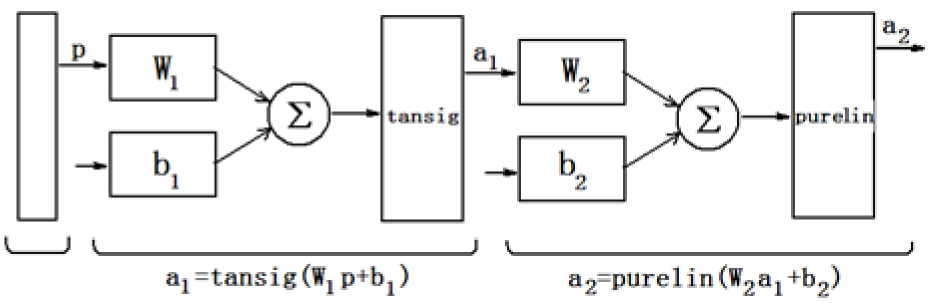


Figure 3. Structure diagram of two layers BP neural network

It is worth noting that, in the design of BP networks, it requires all transfer functions are differentiable, so you can not use hardlim and other binary functions. Commonly used feed-forward BP network transfer function is logsig, tansig, sometimes also used linear function purelin. When a curve function is used in the last layer of the network, the output is limited to a small range, and if a linear function is used, the output can be any value. These three functions are the most commonly used functions in the BP network, but you can create your own other transferable functions if you need to. In addition to the selection of the transfer function, the selection of the number of hidden layer nodes is also important. The selection of nodes needs to be judged according to different training tasks and human experience. Figure 3 is a schematic diagram of a two-layer BP network.

3. The proposed method

3.1 Methodology of this paper

The wavelet analysis method can distinguish the image information from the additive noise in the wavelet domain. The wavelet coefficients of image information are larger, but the number is smaller[6,7]. While the corresponding wavelet coefficients of noise are uniformly distributed, but the amplitude is small. This method can decompose the image, remove the noise in the wavelet domain, and reconstruct the wavelet to get the denoised result.

BP network is a "black box" operating system. The idea of this paper is to build a BP neural network which can denoise in the wavelet domain. The training sample uses a series of original images (no noise) and noise images. Then the wavelet coefficient of the noise image is used as the sample input of the network. The original image Wavelet coefficients as the desired output, then through training can get a network to remove image noise. This network can be used to deal with the noise image, get the denoised image.

3.2 Specific steps

In this paper, we will select the single hidden layer structure of 20 nodes. Specific steps are as follows.

1) Select 10 images, I_1, I_2, …, I_{10} respectively, to add the noise on these 10 images, get noise image, I_1', I_2', …, I_{10}'. The added noise is Gaussian noise of 20db.
2) The original image is decomposed by wavelet, and the wavelet coefficients, Iw_1, Iw_2, …, Iw_{10}, are obtained. The wavelet transform is also applied to the image after adding the noise to get the wavelet coefficients of the noise image, Iw_1', Iw_2', …, Iw_{10}'.
3) Create a BP network and initialize the network. In this paper, BP neural network is chosen to be a single hidden layer structure, and the number of neurons in hidden layer is 20.
4) The wavelet coefficients Iw_i $(1 \le i \le 10)$ of the noisy image are transformed into a row vector and normalized to be the input of the BP network.

5) The wavelet coefficients $Iw_i'(1 \le i \le 16)$ of the original image are transformed into a row vector and normalized as the desired output of the BP network.
6) The BP network is trained with the input and output of 4 and 5, the number of training is 100 and the training goal is 0.01. After the training is finished, get the network.
7) For the image to be processed I, the wavelet coefficients I_w are obtained by wavelet decomposition. Then, according to step 4, a row vector is obtained and normalized.
8) The row vector obtained in the previous step is input to the network, and the output is also a row vector, which is inverse normalized and transformed into a matrix form, which is the wavelet coefficient of the denoised image.
9) The wavelet coefficients obtained in the previous step are reconstructed by wavelet to get the result of denoising.

In this method, it should be noted that the types of samples should be consistent. Different images, features, different strategies to remove noise, no one method can be very good for all types of image noise removed. In this paper, although the type of image is not taken into account in the design process, it is necessary to set the sample image to be consistent in order to better meet the requirements of network training. In this way, different denoising networks are set for different types of images, and the denoising effect can be improved.

4. Experimental results and comparison

The images used in this experiment are SAR images. Its size is 512×512. The added is 20 dB of Gaussian noise. In the experiment, the BP neural network is designed as a single hidden layer structure with 20 hidden nodes, 100 training times, 0.01 training target , $\tan sig$ and *purelin* transfer function, respectively. In this paper, the proposed method is compared with median filtering, Wiener filtering and other methods.

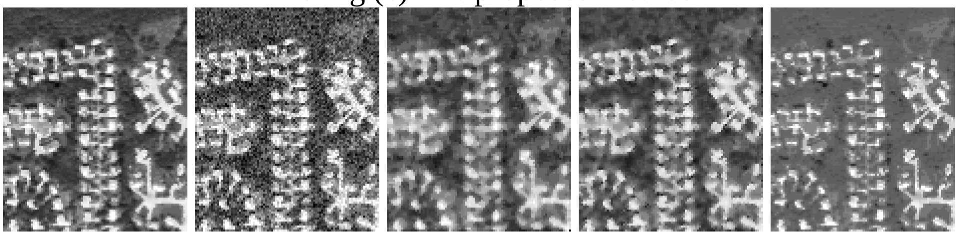
4.1 Experiment One

(a) (b)

Figure 4. Original image and added noise image

(a) (b) (c)

Fig.5 Experimental results of various image denoising methods (a) Median filtering (b) Wiener filtering (c) The proposed method

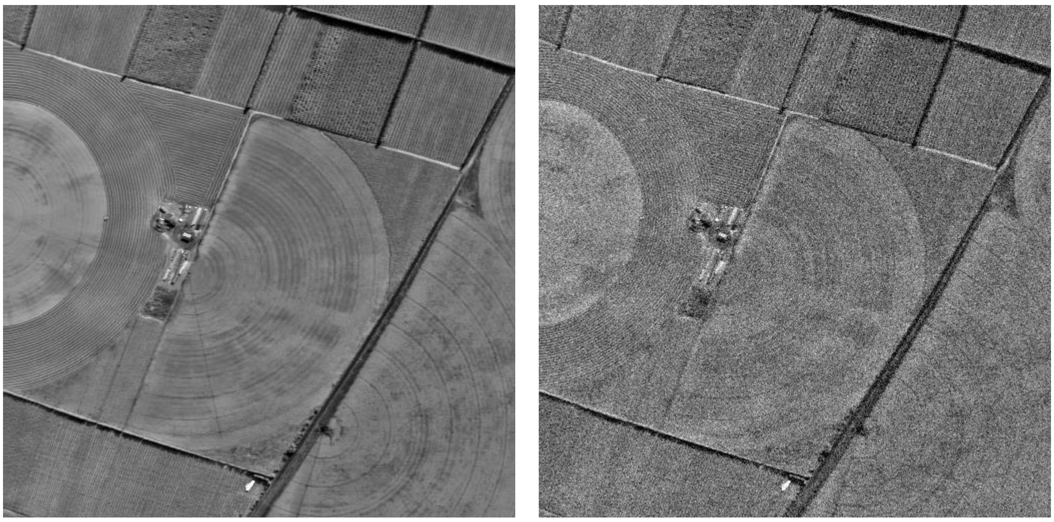


(a) (b) (c) (d) (e)

Fig.6 Comparison between the original image and the noise image and the various image denoising parts. (A) the original image; (b) the Gaussian noise image; (c) the median filter; (d) the Wiener filter;

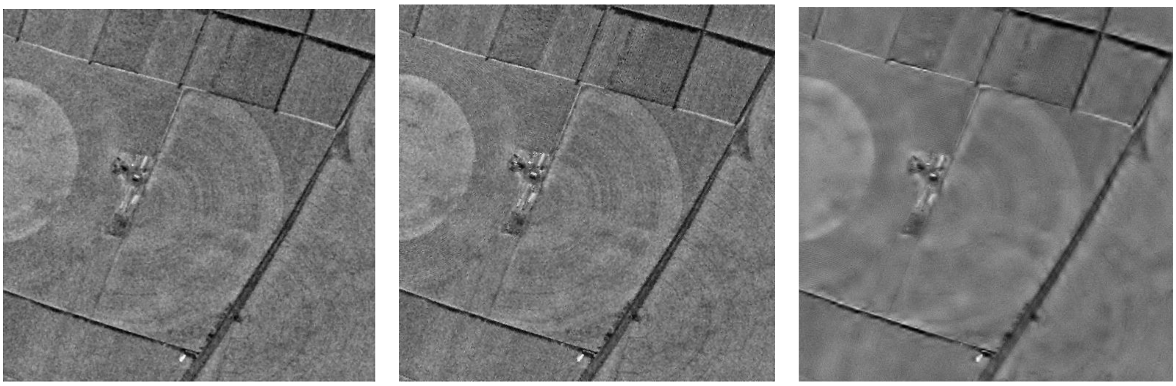
Figure 4 is the original image and the image after adding noise, Figure 5 is the three methods of denoising experimental results. In the original image, there are more detail points, this experiment is to compare the effect of various methods on denoising image with more detail. In order to better compare, a part of the image is extracted, as shown in Fig 6. It can be seen that the median filtering method (c) and the Wiener filtering method (d) obscure the dotted portions when processing the noise, and the method (e) is better and the dotted area is clearer. And from the whole, this method is also better, more smooth, no noise traces.

4.2 Experiment Two



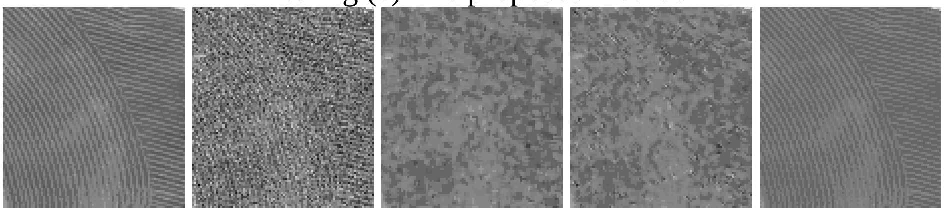
(a) (b)

Figure 7. original image and added noise image



(a) (b) (c)

Fig.8 Experimental results of various image denoising methods (a) Median filtering (b) Wiener filtering (c) The proposed method



(a) (b) (c) (d) (e)

Fig. 9 Comparison between the original image and the noise image and the various image denoising parts. (A) the original image; (b) the Gaussian noise image; (c) the median filter; (d) the Wiener filter; (e) The proposed method

Figure 7 is the original image and the image after adding noise, Figure 8 is the use of three methods of denoising experimental results. The stripe-like details of the original image are more, this group of experiments is to compare the various methods in the stripe-like details of the image denoising effect. Also extract the same parts of the image for comparison. As shown in Fig. 9, due to the addition of noise, the textures are almost invisible in the texture area, so there is no texture in the results of the median filter (w) and Wiener filter (d). However, this method (e) clearly retains the texture.

4.3 Experiment Three

(a) (b)

Figure 10. Original image and added noise image

(a) (b) (c)

Fig.11 Experimental results of various image denoising methods (a) Median filtering (b) Wiener filtering (c) The proposed method

This group of experiments is to compare the results of several methods. Fig. 10 is an original image and an image after adding noise. Fig. 11 shows the denoising results of the three methods. The original image contains various types of areas, including point-like areas, striped areas, smooth areas. In contrast, the proposed method (Figure 11c) performs well, in which regions the noise is well handled and the features of the original image are preserved.

5. Discussion

However, it is worth noting that all of the results of this paper have poor gray-scale properties. This is because the neural network in the training time, just pay attention to each pixel, and does not take into account the overall image gray-scale characteristics. If we can train in the network, adding gray information to guide the training, will be able to improve the effectiveness of this method.

Wavelet denoising method has already been proposed. Hard thresholding and soft thresholding are well established. This paper make an attempt to use of BP network and wavelet analysis method. The time taken to remove noise in this paper is not listed. In fact, the processing time after the denoised network is obtained is very short. The key is to train the network for a long time. For different types of noise, different image types need to train different denoising networks, which makes the overall time is longer. So it is necessary to design a fast BP neural network training method. The design of the hidden layer and transfer function of the BP network need to be improved. Choose what transfer function, the number of hidden layer nodes selected will affect the image denoising effect, which is the next step we should study.

6. Conclusion

The method of image denoising combined with BP neural network and wavelet decomposition, which is different from the traditional filtering method, focuses on the training of neural network by using wavelet decomposition coefficient of original image and wavelet decomposition coefficient of noise image. And get a network to remove image noise.

This method can remove the noise of the image well both in the punctiform region and the striped region, and the effect is better than the traditional denoising method. Of course, as mentioned in the last paragraph of the previous paragraph, this method is not perfect, there are many areas need to be modified, which is the focus of the next paragraph.

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