Research on Denoising Method of Remote Sensing Images Based on Convolutional Neural Network

Rui Jiang

Baise University;Guangxi Baise 533000,China

Keywords: Convolutional Neural Network；Remote Sensing Images；Picture Noise Reduction, Feature Extraction

Abstract. Remote sensing image is different from general image, it has a high feature dimension, and the current remote sensing image detection technology is difficult to express its high-dimensional features well. Once the remote sensing image has noise, the difficulty of feature extraction is further improved. With the continuous development of science and technology, the research of image denoising is not limited to the professional field. Now photography has become an indispensable part of everyone's life, and the demand for image denoising is also increasing. However, there are still some shortcomings in the traditional image denoising algorithm. Based on the above problems, a method of remotely sensed image denoising based on convolution neural network is proposed in this paper. Compared with traditional denoising methods, convolution neural network is more inclined to consider the local spatial characteristics of pictures. Through network training, the features of pictures are learned, and the noisy pictures are compared by using the learned features, so as to achieve the purpose of denoising. Experiments show that the method effectively improves the image quality of remote sensing images and has good noise reduction effect.

1. Introduction

With the continuous development of science and technology, the research of image information processing technology has become in full swing. Among them, image denoising technology, as a basic part of image information processing, has attracted the attention of many experts and scholars at home and abroad. Remote sensing image is one of the most important means to reflect the features of terrain. The shape and texture of real terrain can be effectively judged by remote sensing image, as well as the height of terrain. However, remote sensing images will be affected by many factors in the process of acquisition and transmission, resulting in a lot of noise, which seriously affects the analysis of remote sensing images by professionals. Therefore, denoising of remote sensing image becomes very important.

The purpose of image denoising is to make the original image free from noise and to prevent the influence of noise on the judgement of researchers. In recent years, many advances have been made in denoising algorithms for remote sensing images. Nowadays, there are many kinds of denoising applications in remote sensing images: in literature [1], residual learning and batch normalization are used to speed up the training process and improve the denoising performance. In the literature [2], the author uses a small sample size and convolution layer to construct an automatic de-noising coder for effective denoising of medical images. In reference [3], a new depth network architecture for gray and color image denoising based on non-local image model is proposed. In reference [4], the author proposes a fast and flexible denoising convolution neural network, FFDNet, with adjustable noise level map as input. In [5], a more flexible model, weighted Schatten p-norm minimization (WSNM), is proposed to generalize the NNM with different singular values into Schatten p-norm minimization for image denoising. In recent years, the application of convolutional neural network is more and more. In [6], we propose a new algorithm based on deep convolution neural network (CNN) to solve the inverse imaging problem. In [7], the author applies convolutional neural network to music label classification. In literature [8], in order to eliminate these complex motion blurring, the author proposes a multi-scale convolution neural network, which can restore clear images in an end-to-end manner. In the literature [9], the author used

  DOI: 10.25236/ciais.2019.034

convolutional neural network to classify pulmonary tuberculosis automatically and the effect was remarkable. In the literature [10], DeepFix, a completely convoluted neural network, is proposed for understanding and predicting the mechanism of human visual attention. This network can significantly predict the mechanism of visual attention.

In this paper, the convolution neural network is used to denoise remote sensing images, and a symmetrical network is constructed by constructing convolution subnetwork and deconvolution subnetwork. By comparing the network structure with different convolution layers and the commonly used denoising algorithms, the convolution neural network structure adopted in this paper has better denoising performance and faster running speed.

2. Method

2.1 Convolutional Neural Network. Convolutional neural network is an artificial network, which is widely used in image processing, speech recognition, natural language processing and other fields, and the effect is remarkable. The characteristic of convolutional neural network is that it is a weight-sharing network. Compared with MLP and DBN in deep learning, it has fewer adjustable parameters and lower learning complexity. It is noteworthy that the convolution neural network has a high degree of invariance to the tilt, scaling and translation of two-dimensional images.

2.2 Remote Sensing Image Denoising Based on Convolutional Neural Network. The purpose of image denoising is to restore the original image information corroded by noise.The expression is:

$$g(x, y) = f(x, y) + \eta(x, y) \qquad (1)$$

Among them, $g(x, y)$ representation the remote sensing image with noise, $f(x, y)$ representation the original image without noise and $\eta(x, y)$ representation the added noise are used. By adding noise to the original image and training the convolution neural network, an estimate of the original image is learned, which makes the image with noise closer to the original image.

2.3Network Structure of Convolutional Neural Networks. In the design of convolutional neural network for image denoising, the relationship between noisy images and denoised images should be fully considered. That is to say, the network is a non-linear mapping relationship between noisy images and denoised images. Constructing a convolution network needs to include input layer, convolution layer, activation layer, pooling layer, full connection layer and so on.

The characteristics of the network are as follows:

1) image input and output. The structure of the neural network in this paper takes the original picture as input, and produces a complete image output through the convolution neural network. Direct input image eliminates complex image preprocessing process and improves work efficiency.

2) Nonlinear relation mapping. In this paper, we construct a network structure with convolution filters of different sizes. This structure can share the training weight parameters well, and learn the non-linear mapping relationship between graph and graph.

3) Learning. This paper is different from the original batch learning method, but adopts fragmented learning, which greatly improves the efficiency of learning.

3. Experiment

In order to prove the denoising effect of the convolutional neural network proposed in this paper, we choose VOC2012 data set for training, randomly select 10 000 pictures from the data set for training, and add noise interference to 1000 of them. An example of adding noise is shown in Figure 1.

1) original remote sensing imag 2) remote sensing image after adding noise

Figure 1. Contrast before and after processing remote sensing map

The input and output data used in this training are all selected from the remote sensing image fragments, and the sliding window method is used to select the fragments. In order to enhance the learning ability and generalization ability of the model, the noise-added image fragments have been mixed with the noise-free data for model training.

4. Result

Result 1 Denoising ability is closely related to network structure.

In order to study the influence of different network structures on denoising ability, we try to use different convolution core sizes and convolution layers to carry out experiments, and record the experimental results. According to the experiment, we get the following experimental data, as shown in Table 1 below:

Table 1 Deenergization comparison under different network structures

Layer number	Convolution kernel	Number of feature map	Average PSNR/dB	Average time consuming/s
4	3x1x3	1x32x32x1	25.82	0.24
4	5x1x5	1x32x32x1	26.17	0.33
4	5x1x5	1x64x64x1	27.73	0.45
5	5x3x3x5	1x32x64x32x1	28.17	1.09
6	5x3x1x3x5	1x32x64x64x32x1	28.57	1.36

From Table 1, we can see that the increase of convolution layer can improve the denoising ability of remote sensing image to some extent, but the increase of convolution layer means that the more model parameters, the higher time complexity. Experiments show that it only takes 0.3 s to process a 512 x 512 remote sensing image in a four-layer convolution network structure, but when the number of layers increases to 6 layers, it takes 1.5 s and increases exponentially. On the other hand, the denoising effect is also affected by the size of convolution kernel and the number of feature maps. In the experiment, we can see that each feature map obtains different features of the image, so increasing the number of feature maps to a certain extent can improve the learning ability of image features and achieve better denoising performance.

Result 2 Comparison of results from different algorithms.

In order to demonstrate the superiority of convolution neural network in remotely sensed image denoising, we selected 5 images for simulation test, and compared the final denoising results with the existing algorithms with higher performance. In this experiment, we add Gauss white noise of $\sigma = 22$ to all the test pictures. All the algorithms are processed by CPU only. The peak signal-to-noise ratio (PSNR) is selected to evaluate the denoising effect. The experimental

environment was Ubuntu 15.04, Intel Core i7, Python 3.7. The experimental results are shown in Table 2 below.

Table 2 Comparison of PSNR denoising by different methods（σ=22）

image	Noise	GSM	KSVD	CN2	MLP	This article method
House	20.23	32.10	32.21	31.31	32.48	32.50
Montage	20.77	29.35	30.53	30.80	31.34	31.85
Peppers	20.32	29.39	29.63	29.55	30.12	30.49
Lena	20.22	31.27	31.31	31.01	32.09	31.94
Boat	20.26	29.30	29.32	29.13	29.84	29.85

From Table 2, we can see that PSNR is better than GSM, KSVD, CN2 and MLP at the noise level of $\sigma = 22$. In this paper, different convolution neural networks are constructed by changing the size of convolution kernels and the number of feature graphs, so the denoising time is less than that of CN2, and the deconvolution layer proposed in this paper has remarkable denoising effect. MLP uses four layers of fully connected neural network structure to process image fragments. At last, it uses a lot of time to generate the denoised image by splicing and fusing all the processed images. Compared with MLP, this method has no size limitation on the input and output images, and avoids the steps of image preprocessing. The output image is also the same as the input size, so the denoising time is less.

5. Conclusion

Image denoising plays an important role in the analysis and processing of remote sensing images. By denoising remote sensing images, researchers can more easily read the information of remote sensing images. In this paper, the denoising method based on convolution neural network is used to denoise remote sensing images. The influence of data set composition and model structure on denoising results is analyzed through experiments. The experimental comparison shows that the denoising method proposed in this paper has different degrees of improvement compared with the current commonly used and better denoising algorithms. The denoising effect is considerable and the denoising process is consumed. It's shorter.

References

[1] Zhang K, Zuo W, Chen Y, et al. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising[J]. IEEE Transactions on Image Processing, 2017, 26(7): 3142-3155.

[2] Gondara L. Medical image denoising using convolutional denoising autoencoders[C]//2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW). IEEE, 2016: 241-246.

[3] Lefkimmiatis S. Non-local color image denoising with convolutional neural networks[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017: 3587-3596.

[4] Zhang K, Zuo W, Zhang L. FFDNet: Toward a fast and flexible solution for CNN-based image denoising[J]. IEEE Transactions on Image Processing, 2018, 27(9): 4608-4622.

[5] Xie Y, Gu S, Liu Y, et al. Weighted Schatten $ p $-norm minimization for image denoising and background subtraction[J]. IEEE transactions on image processing, 2016, 25(10): 4842-4857.

[6] Jin K H, McCann M T, Froustey E, et al. Deep convolutional neural network for inverse problems in imaging[J]. IEEE Transactions on Image Processing, 2017, 26(9): 4509-4522.

[7] Choi K, Fazekas G, Sandler M, et al. Convolutional recurrent neural networks for music classification[C]//2017 IEEE International Conference on Acoustics, Speech and Signal

Processing (ICASSP). IEEE, 2017: 2392-2396.
[8] Nah S, Hyun Kim T, Mu Lee K. Deep multi-scale convolutional neural network for dynamic scene deblurring[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017: 3883-3891.
[9] Lakhani P, Sundaram B. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks[J]. Radiology, 2017, 284(2): 574-582.
[10] Kruthiventi S S S, Ayush K, Babu R V. Deepfix: A fully convolutional neural network for predicting human eye fixations[J]. IEEE Transactions on Image Processing, 2017, 26(9): 4446-4456.