Rock Thin Section Image Classification Research from Shallow Network to Deep Neural Network

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Abstract. Image classification technology has made tremendous progress with the development from shallow network (neural network) to deep neural network, image classification based on deep neural network has become popular in the field of image classification technology. By introducing shallow network and deep neural network, and making classification for 30 rock thin section images and contrast according to connectivity of pores with examples of the BP neural network (hidden layer has 6 neuron nodes and 7 neuron nodes) from shallow network and the convolutional neural network from deep neural network, finally, the average error rate of classification for deep neural network is 0%, and the average error rate of classification for BP neural network are 24.666% and 19.334% respectively, which shows that rock thin section image classification based on deep neural network has higher efficiency and better classification result than rock thin section image classification based on shallow network.

Introduction

With the development of computer technology, the technology of image classification continues to progress, the technology of image classification based on shallow network has matured, while the technology of image classification based on deep neural network has become popular in the field of image classification.

Rock thin section image classification is reflected differently features, according to scene or target of rock thin section images, and then make classification and recognition of rock thin section images. The computer can identify the category to which it belongs according to the rock thin section image properties when it was given a rock thin section image, and then achieve the purpose of understanding the image. Rock pores are not only the storage space of oil and gas, but also their passage. It has a very important practical significance to the oil industry that research pore structure of rocks and make classification of rock thin section images.

Rock Thin Section Image

Rock thin section images are images which are shot from rock thin sections with a microscope. Rock thin section is a small piece of rock thin section which is cut from rock sample, stuck on slide and ground it into micron thick [1]. The mainly parts of rock thin sections are rock particles, pores and debris. Pores in rock thin sections used in this study were injected with blue gels [2].

This study will make classification of 30 rock thin section images according to connectivity of pores, which will be finally classified into two categories that is good connectivity and poor connectivity. The supervised training method was used for this paper, so the pores connectivity of images have been classified in accordance with the sum of pores area of images, a large area for good

connectivity, and a small area for poor connectivity. There are 15 images of good connectivity and 15 images of poor connectivity, test images are training images.

Shallow Network and Deep Neural Network

Shallow Network and BP Neural Network. Shallow network, is also known as artificial neural network (ANN). Among them, BP neural network is the essence of the whole ANN system. BP neural network consists of input layer, hidden layer and output layer, the hidden layer may be one or more layers. BP neural network has the following characteristics:

(1). Network composed of multiple layers, all connections between layer and layer, no connection between neurons in the same layer.

(2). The transfer function of BP neural network must be differentiable.

(3). Using the error back propagation algorithm to learn.

Development from Shallow Network to Deep Neural Network. Feature extraction is the most critical step in image classification. Shallow network is artificially selected characteristics, it is time-consuming and laborious. In recent years, some researchers have developed a number of methods that can automatically learn characteristics from images that was called deep learning (DL). In 2006, Hinton and his student whose name is Salakhutdinov raised the concept of deep learning in a paper entitled “Reducing the dimensionality of data with neural networks” [3].

Deep Neural Network and Convolutional Neural network. DL is characterized by a plurality of hidden layers. On the basis of the pixels of original input images, DL will get more and more abstract features through learning layer by layer, that is a combination of low-level features to form a high-level feature [4]. Finally, we use the features which DL has learned to classification. DL is very similar to the stage treatment of visual information of human visual system [5].

The common methods for DL are convolutional neural network (CNN), deep belief network (DBN), restricted boltzmann machine (RBM) and so on. Take CNN as an example to explain. CNN is a multilayer neural network, each composed of a plurality of two-dimensional planes, and each plane composed of a plurality of individual neurons [6]. Fig. 1 is a structural diagram of CNN.

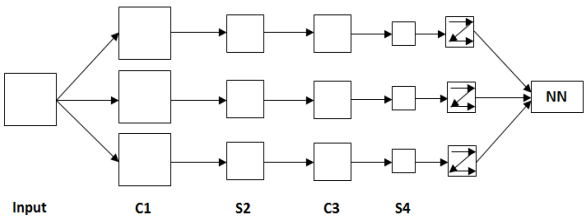

Figure 1. A structural diagram of CNN

Initially, CNN executes a convolution operation of input images and three filters, C1 layer is displayed the three feature maps after the convolution operation. Then, CNN processes each pixel on a feature map, and gets three new feature maps displayed in the S2 layer through summing, adding weights, adding bias and sigmoid function. And then, CNN executes filtering process to the feature maps on S2 layer, now, C3 layer is obtained. And S4 layer is obtained by the same principles and operations as before. Finally, the pixel values are rasterized and combined as the input of the neural network, and ultimately get the output [7].

The structure of CNN has an advantage of displacement invariance, and the biggest advantage of CNN is the reduction of the number of parameters of neural network training needs through weights sharing and receptive field [8].

Difference between Deep Neural Network and Shallow Network. (1). It can automatically learn more effective characteristics representation through DL [9, 10]; but the feature extraction of ANN is artificially selected.

(2). The complex function representation of CNN has better effect and higher efficiency than ANN.

(3). The training process of DNN is that it executes unsupervised learning from bottom to top and then executes supervised learning through the way from above to below; ANN adopts back-propagation (BP) manner as its training way.

Rock Thin Section Image Classification Based on BP Neural Network

Design of BP Neural Network. (1). The number of network layers: 3. The number of Sample images is small, it is not necessary to add hidden layers to reduce the scale of network, so the BP neural network which is used in this paper contains only one hidden layer.

(2). The number of neuron nodes of input layer: 7. The input of BP neural network is features of images. In this experiment, each image is extracted a 7-dimensional feature vector, and the dimension of feature vector determines the number of neuron nodes of input layer. In this experiment, feed forward net function in the new version neural network toolbox of matlab is used to create network, when we use this function to create a BP neural network, the input vector dimension defaults to 0, and the dimension of vector is determined by the given training data when we use train function to train.

(3). The number of neuron nodes of hidden layer: 6 or 7.The number of neuron nodes of hidden layer is estimated by the empirical formula. In this experiment, we adopt the Eq. 1 as the empirical formula:

$$\sum_{i=0}^{n} C_M^i > k \,. \tag{1}$$

In the above formula, k is the number of samples, M is the number of neuron nodes of hidden layer, n is the number of neuron nodes of the input layer. If $i > M$, we set $C_M^i = 0$.

(4). The number of neuron nodes of output layer: 1. Before the experiment, all the images have been classified into two classes, the desired output of an image which has good pore connectivity is 1, the desired output of an image which has poor pore connectivity is 0. When we use feedforwardnet function to create a BP neural network, the output vector dimension defaults to 0, and the dimension of vector is determined by the given expected output when we use train function to train.

(5). The option of transfer function: hidden layer adopts sigmoid function, output layer adopts linear function, and then output results are rounded to give the final result as 0 or 1.

(6). The option of training method: LM algorithm. LM algorithm is the improved algorithm of standard steepest descent BP method, its convergence rate is faster than standard steepest descent BP method.

Experimental Procedure. (1). Importing image. The original image is 1560×1920 pixels, all the original images are scaled to 120×480 pixels.

(2). Image segmentation. Using the otsu function, which is to use gray thresh function to obtain a global threshold, then use im2bw function for image segmentation. Then we adopt color inversion operation. The basic principle of otsu algorithm is that classify the gray values of image into two parts based on the optimal threshold, so it can make the maximum variance between the two parts, that is the two parts have the greatest separation.

(3). Feature extraction. 7-dimensional column vectors are extraction in this experiment. The first dimension of feature is the number of pixels which pixel values are 1, which is pores area. The method is that adopt bw label function to mark 8-connected fields in images, and adopt region props function to find the number of connected fields (pores), and then obtain the sum of areas of all the connected fields, which is considered as the pores areas of rock thin section images. Then the images are classified into four blocks, which are the top left corner, top right corner, lower left corner and lower right corner. The second, third, fourth and fifth dimension of feature are the number of pixels which pixel values are 1 of the top left corner, top right corner, lower left corner and lower right corner rectangular blocks in images respectively. The sixth dimension and seventh dimension of

feature are the number of pixels which pixel values are 1 of the parts of 1/3 to 2/3 of vertical direction and horizontal direction in images. Finally, all the feature column vectors are arranged for a feature matrix in order of left to right.

(4). Normalization. The feature matrix is normalized by map min max function, which is to be the input of BP neural network.

(5). Creating, training and testing BP neural network.

(6). Calculating the error rate of classification.

Experimental Results. The testing results are shown in Table 1. After calculation, the average error rates of classification through training and testing five times for the BP neural network in which hidden layer has 6 neuron nodes and 7 neuron nodes are 24.666% and 19.334% respectively.

Table 1 The testing results of BP neural network

The error rate of BP neural network in which hidden layer has 6 nodes					The error rate of BP neural network in which hidden layer has 7 nodes				
The first time	The second time	The third time	The fourth time	The fifth time	The first time	the second time	The third time	The fourth time	The fifth time
20.00%	46.67%	10.00%	43.33%	3.33%	46.67%	20.00%	10.00%	6.67%	3.33%

Rock Thin Sections Image Classification Based on Convolution Neural Network

In this experiment, the convolution part of CNN is designed as 6C-2S-12C-2S structure, the tail part of CNN is designed as a single layer perceptron, the final output of classification result of a image is 0 or 1 (0 represents the rock thin section image which has poor pore connectivity, 1 represents the rock thin section image which has good pore connectivity).

Experimental Procedure. (1). Importing images. The original image is 1560×1920 pixels, all the original images are scaled to 120×480 pixels.

(2). Normalization. All the data are divided by 255.

(3). Setting network structure and parameters of training. C1 layer obtains 6 2-dimensional feature maps by convolution operation of input image and convolution kernel of 5×5 size, the sizes of 6 2-dimensional feature maps are (120-5+1) $\times$ (480-5+1) =116×476. 6 feature maps of sizes of 58×238 in S2 layer are obtained through summing all the non-overlapping sub-blocks of sizes of 2×2 in C1 layer, and the sum is multiplied by a weight w (we set was a random number between -1 and 1 in this experiment), and then the product plus a bias b (we set b to 0 in this experiment). The inputs of S2 layer are combinations of several feature maps or all feature maps, and the combinations are executed convolution operation with convolution kernel of 5×5 size, then 12 feature maps of (58-5+1) $\times$ (238-5+1) =54×234 size in C3 layer are produced. 12 feature maps of 27×117 size in S4 layer are obtained through summing all the non-overlapping sub-blocks of 2×2 size in C3 layer, and the sum is multiplied by a weight w, and then the product plus a bias b. Learning rate is set as 1, the number of training samples is 30, the number of iteration is 1.

(4). Initializing the parameters of CNN. The parameters of CNN include size of feature maps in every layer, convolution kernel, bias, the parameters of the single layer perceptron, and so on.

(5). Batch training and testing CNN.

(6). Calculating the error rate of classification.

Experimental Results. The designed CNN is trained and tested five times, the testing results are shown in Table 2, and all of the error rates are 0%.

Table 2 The testing results of CNN

The error rate of CNN				
The first time	The second time	The third time	The fourth time	The fifth time
0%	0%	0%	0%	0%

The Comparison and Analysis of the Experiments of BP Neural Network and CNN

Before rock thin section image classification with BP neural network, we need to obtain features of every image by artificial extracting. The process of feature extracting is time-consuming and laborious. But it has no need of features by artificial extracting to CNN, it can automatically learn features of rock thin section images and classify each image.

From Table 1 and Table 2, we can see that the effect on rock thin section image classification based on CNN is better than BP neural network.

Summary

In 2012, the error rate of image recognition review on ImageNet has been reduced from 26% to 15%. In 2013, DL model has been successfully applied in recognition, classification and understanding of general images. In March this year, AlphaGo proved great potential of DL by go. Thus, DL gets more and more attention from researchers.

Learning DL model features, we can overcome problems of time-consuming and laborious in artificial extraction, and can obtain more efficient expression of images. Compared with shallow network, we can obtain a higher efficiency and better rock thin section image classification result by CNN. There will be more and more researches on rock thin section image classification based on DNN.

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