The Volcanic Rock Is Identified Automatically Using the Convolutional Neural Network

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Abstract. According to the well logging, drilling, and 3D seismic data, we identified the volcanic rock automatically by computer. The recognition system was an image recognition technology based on deep learning algorithm based on seismic data. During the identification process, the 3d seismic data are disassembled into 2d seismic profile by seismic interpretation technique in Dehui Fault Depression of Songliao Basin. And then, we think it was a two-dimensional picture as learning samples, classification of seismic data, establishment of labels, forming a training set. The training set is deeply learned to generate automatic recognition model. Finally, according to the generated automatic identification model, the volcanic rock is realized automatically based on seismic data.

Keywords: Volcanic Rock, Seismic Image, Deep Learning, Dehui Fault Depression

1. Introduction

The lithology and facies of volcanic rocks change rapidly and are affected by volcanic eruption, transportation and emplacement conditions, they are strong heterogeneity. Volcanic rock is composed of multi-mechanism, multi-cycle and multi-period, and its distribution space is limited and overlapped longitudinally. The recognition system was an image recognition technology based on deep learning algorithm based on seismic data. During the identification process, the 3d seismic data are disassembled into 2d seismic profile by seismic interpretation technique in Dehui Fault Depression of Songliao Basin. And then, we think it was a two-dimensional picture as learning samples, classification of seismic data, establishment of labels, forming a training set. The training set is deeply learned to generate automatic recognition model. Finally, according to the generated automatic identification model, the volcanic rock is realized automatically based on seismic data. The structure of the system is as follows:
2. Deep Learning Technology

Deep learning is a neural network and a new field in machine learning field, which motivation simulates the human brain for analytical learning. It simulates the mechanism of human brain to interpret something, such as pictures, words and so on. Deep machine learning methods are divided into two categories, which is supervised learning and unsupervised learning. For instance, convolutional neural networks is a deep supervised learning model, however, deep belief nets is a unsupervised learning model.

The idea of deep learning is derived from the development of artificial neural networks. One of the important structures of deep learning is the multi-layer perceptron. Here's how deep learning works: it learned the low-level features firstly, and found the distribution of data, and combined to complete the abstract high-level features finally. Hinton et al put forward the concept of deep learning in 2006, and proposed an unsupervised layer by layer training algorithm which is based on deep confidence network (DBN)[1-3]. In order to solve the problem of deep structure optimization, the deep structure of multi-layer automatic encoder is proposed. The convolutional neural network proposed by Lecun et al is the first real multi-layer structure learning algorithm, which uses spatial relative relation to reduce the number of parameters to improve training performance. In addition, convolutional neural network is a real multi-layer structure learning method, which take advantage of spatial relations to reduce parameters to improve the training ability [4-6].

Deep learning solves the following problems of neural network: the problem of insufficient depth; The cognitive process needs to be carried out layer by layer and complicated step by step. In many cases depth is sufficient to represent any function with a given target accuracy. But the price is that the number of nodes required (such as calculations and parameters) can become very large. Theoretical results confirm the existence of a family of functions in which the number of nodes actually required grows exponentially with the size of the input. We can think of depth architecture as a kind of factorization. Most randomly selected functions cannot be efficiently represented, either in deep architecture or shallow one. However, most of the functions can be efficiently represented by deep architectures can't be efficiently represented by shallow architectures. The existence of a deep and tight representation means that there is some structure in the potentially representable function. If you don't have any structure, you can't generalize very well.

Training the depth architecture had failed before 2006, training a deep supervised feedforward neural network tended to lead to a bad ending, which means not only in training but also in testing errors, ultimately shallower it to 1 or 2 hidden layers. Until 2006, the revolutionary research led by Hinton et al., came to light. Nowadays, after more than ten years of rapid development, deep learning technology has been applied to computer vision widely, speech recognition, text recognition, and in the medical equipment, geological exploration and other areas of exploratory applications.

In this paper, the algorithm of convolutional neural network (CNN) is adopted. CNN is a
multi-layer neural network, which is skilled in processing machine learning problems of images, especially for the huge images. CNN has a series of methods; it reduces the dimension of image recognition problem and achieves the purpose of training successfully. This network is called LeNet, and its structure is below:

![The structure of convolutional network](image)

**Figure 2. The structure of convolutional network**

LeNet is a typical convolutional network. It contains convolution layer, pooling layer, fully connected layer. The convolution layer cooperates with the pooling layer to synthesize multiple convolution groups, which can get image features exactly layer by layer, and achieve classification finally [6-9].

To sum up, CNN relies on convolution to simulate image features, and reduces the number of network parameters through the way of weight sharing and pooling. It completes the classification task by means of traditional neural network finally. The Convolution layer is used for local feature extraction, and the Convolution Kernel, also called filter, is the core of Convolution operation. The convolution kernel is represented by the corresponding weights W and the offset b and here is the convolution kernel of 3x3 convolving over the image of 5x5, which is the sum of the matrix dot products.

Pooling layer is a process of dimensionality reduction, which mainly focuses on the result of convolution operation. It is simply to say the down sampling. For example, the original image was 20x20, and we sampled it down with a sampling window of 10x10, and finally turned it into a feature graph of 2x2 size. The reason for this is that even after the convolution, the image is still large (because the convolution kernel is small), so for the sake of reduce the dimension of the data, we sample it down. This can be done because the statistical properties of the feature can still describe the image, even with much less data, and because the reduction of the data dimension effectively avoids overfitting. In practical application, Pooling can be divided into max-pooling and mean-pooling according to the method of lower sampling.

3. **Training Set Expansion**

In practical work, we find that the existing seismic data cannot form enough training set, so we need to expand the existing samples. The extended algorithm is based on the rigid preserving image transformation to carry out random transformation of the existing two-dimensional seismic images. The rigid-preserving image transformation has two steps:

The first step is to ensure that before and after the deformation, each triangle is similar to the original triangle, which is also called the similar-preserving deformation of the grid model.

The second step is to ensure that each triangle is as congruent as possible with the original triangle. Since the algorithm in the first step only keeps the similarity, some triangles will be enlarged and some will be reduced after deformation, resulting in local image amplification and reduction. Therefore, it is necessary to make appropriate scaling adjustments for each triangle. This step is also known as the fitting step.

The transformation effect of rigid graph is shown as follows:
4. Tagging Systems and Knowledge Management

Deep learning requires classification and identification of training samples, and then training and identification based on labels. In the preliminary implementation and testing of the system, we established two basic labels: volcanic rock label and non-volcanic rock structure label.

Based on the algorithm, the recognition accuracy is 65%, that is, for a given unknown volcanic rock (100% contains volcanic rock), the algorithm considers that the average probability of containing volcanic rock in a given seismic image is 60% (not the accuracy rate is 65%). Due to the insufficient number of samples, the reliable accuracy of the algorithm cannot be given in the test, but. We think this result leaves room for improvement. Therefore, we make the following improvements to the label:

![Figure 3. The transformation of rigid image](image)

- The interior of volcanic rock
- The boundary of volcanic rock
- The exterior of volcanic rock

![Figure 4. The example of improved tag](image)

Based on the following labels, the accuracy of the interior identification of volcanic rock has increased to 70%, and the accuracy of the boundary identification of volcanic rock has reached more than 75%. We believe that the improvement in recognition accuracy is due to the following reasons:

Distinguish and identify the interior, boundary and exterior of volcanic rocks, which is beneficial to increase the sample size: for a volcanic rock, multiple samples can be taken inside, instead of recognizing the whole volcanic structure as a whole.

Reduce the error caused by image distortion in the sample database: the increase of initial samples can reduce the number of deformation, thus reducing the error caused by deformation.

In addition, the difference between volcanic rocks, the internal boundary and external, is conducive to further calibration volcanic rock boundary: algorithm's goal is to automatically identify volcanic rocks and demarcate its border, the improved algorithm will be split into smaller earthquake imaging figure yuan, and the identification, classification, and not as a whole, it can realize the border of volcanic rock initial defined.

5. Conclusion

Based on the above phenomenon, We firmly believe that deep learning technology can simulate the human brain's thinking process, is a fully open system, although its technology for applications with the seismic interpretation of volcanic rock identification and target we can't happen overnight, but, as we will be more geological knowledge integration into the system, deepen the combination of the two disciplines in chengdu, we can get more accurate and reliable results, improve the usability of the system and can guide lines, is expected to be in the field of volcanic rock reservoir seismic interpretation and make a new train of thought.
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