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Lithology Recognition Method of Core Image Based on Deep Learning

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ABSTRACT

Lithologic identification of strata is the basic object of petroleum geology research, which can accurately and directly reflect the distribution of oil and gas reserves in the strata and point out the direction for deep petroleum exploration and development. But the early lithologic identification is to use the method of artificial visual observation and manual identification to study the core, which can not guarantee the accuracy and speed of core identification. Based on the achievements of machine learning in the field of image processing and analysis, this paper starts with machine learning, and uses the advantages of machine learning, which can automatically extract features without the influence of external factors to extract the features needed for rock debris recognition, and constructs a three-layer convolution neural network, Finally, a high-precision model for classification and recognition of rock cuttings is trained.

Keywords: CNN, convolution neural network, core recognition, machine learning.

1. Research background and significance

A lot of research and exploration results show that the core is a kind of complex porous medium. The judgment of core type depends on the joint action of many factors such as grain size, pore structure, fracture ratio and shale content. It can be seen that the complexity of rocks is far beyond our imagination, which brings great difficulties to the exploration and development of oil and gas fields.

There are three widely used methods to analyze the microstructure characteristics of cores. The basic vision extraction is the primary operation and extraction of image pixels. For example, the image pixel gray, edge or color distribution statistics, description of the target shape, image texture and so on. The most common features are color, texture and local features. Visual feature expression is based on the basic visual extraction and then carries on the statistics, vector quantization, coding, kernel description or other expression methods, so as to obtain more effective image feature description and form the final image feature. Both basic visual extraction and visual feature representation need to extract features manually. This requires a lot of time and experience, and usually requires professional knowledge and experience. Moreover, there are many defects in artificial design, which are easily affected by subjective factors, especially by the control of human visual resolution, so that the extracted information and analysis conclusions are affected or there are errors, thus affecting the final classification results. In view of the above situation, deep learning which can automatically learn features from images is proposed. Compared with the previous single-layer network, deep learning creates a multi-layer network structure. Nowadays, the widely used deep learning frameworks include the framework based on RBM, the framework based on DBN and the framework based on CNN. This paper chooses convolution neural network framework as the basic classification framework.

2. Principle of core image recognition model

The convolution neural network (CNN) used in the core image recognition model is a multi-layer structure. It can extract the features of the input image through the alternately connected convolution layer and pooling layer, and then get the highly abstract feature image. Finally, the features of the whole original image are classified and expressed through the full connection layer. Convolutional neural network includes input layer, convolution layer, pooling layer, full connection layer and output layer.

The convolution layer contains several convolution kernels, which are equivalent to an n * n weight matrix. When the convolution layer receives the input image from the input layer (the image will be expressed in the form of a pixel matrix), the convolution kernel will slide on the pixel matrix with a fixed step size to convolute each region of the pixel matrix one by one. Each convolution kernel can generate a channel of the input image, and each channel represents a feature image of the input image. Therefore, after convolution operation of the convolution layer, the input image will output a group of filtered feature images.

Pooling layer is also called down sampling layer in convolutional neural network, which is mainly used to reduce the spatial dimension of image features, compress data and improve the processing efficiency of the model. There are two common pooling methods for pooling layer: maximum pooling and average pooling. Maximum pooling is simply to select the maximum value of each region.

3. Realization process of core image recognition

3.1 Select sample data

The sample data is composed of a large number of high-definition core images captured by the core image high-resolution acquisition instrument. These core images are classified according to the description of the core, and labels are made for each core image. Then according to the sedimentary rock categories and the types of existing core images, the core images are divided into clastic rock, clay rock, carbonate rock, sandstone, sandstone and sandstone as shown in Figure 1 Other endogenous rocks. Each class has 500 core images as shown in Figure 2, which are used as the basic data of the lithologic identification model of the core image.

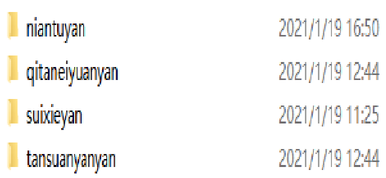

Figure 1 Core Types

Figure 2 Single Class Core Image

3.2 Sample data preprocessing

Before the model is constructed, the core image needs to be preprocessed to minimize the noise of sample data and retain the details of the image as much as possible, so as to prevent noise affecting the selection of image features and errors in the training process.

3.2.1 Unified sample image

Firstly, the size of the sample image must be unified. If the dimension of input vector is not fixed, the quantity of the weight parameters of the whole connection is also not fixed, which will cause the dynamic change of the network and can not achieve the purpose of parameter training. Therefore, through processing, the selected sample image set is unified to 200 * 200 core image.

3.2.2 Image enhancement

Secondly, due to the lack of light or the surrounding environment, the target image is not very ideal. As shown in Figure 3, the extracted feature noise is very large. Therefore, in order to better extract the features of the core image and get a better training model, we need to use image enhancement technology to further process the image to get better features and visual effects as shown in Figure 4.

Figure 3 Original Core Image

Figure 4 Enhanced Core Image

3.3 Construction of core recognition model

The key step of core image recognition is the construction of convolution neural network model. In this paper, through the three convolution pooling process, we get more obvious core image characteristics. In this paper, convolution neural network model is selected, including filling, convolution operation, activation function, pooling, full connection and classification. Each complete core image is divided into many small parts, the characteristics of each small part of the core are extracted, and then the characteristics of these small parts are summarized together, the process of image recognition can be completed.

3.3.1 Filling

For the core image input to be convoluted, the number of pixels in the corner or edge of the image is relatively small. This will weaken the edge information of image recognition. Therefore, before convolution, the core image should be padded, that is, the p-layer data should be filled around the original image data. As shown in the figure below, when the filled data is 0, it is called zero padding. In addition to preserving more effective information, padding operation can also ensure that the height and width of the volume do not change before and after convolution calculation.

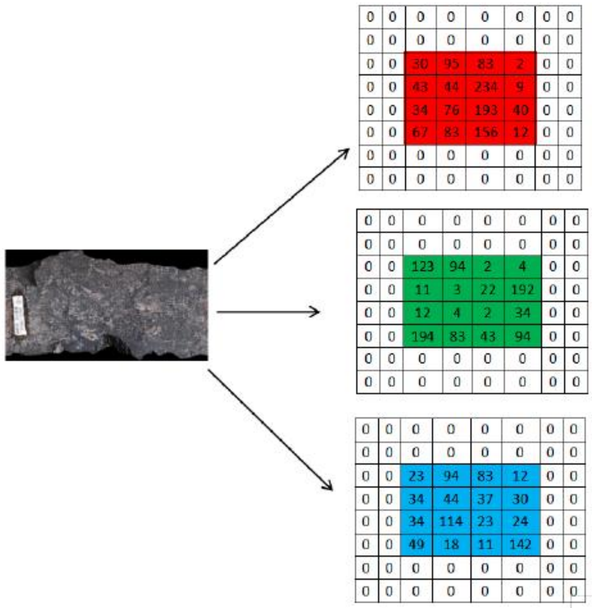

Figure 5 filling of input image

3.3.2 Model building process

The first convolution pooling is mainly to process the original core image. Because the sample set of the core image unifies the size of the image through preprocessing, which is 200 * 200 core image, and the color feature of the core image is also an important feature of lithology recognition, there are three color layers R, G and B. In this way, the core image size of the accurate sample set is 200 * 200 * 3. In the case of the same receptive field, the smaller the convolution kernel is, the smaller the parameters and computational complexity are. Convolution kernel size must be greater than 1 to enhance receptive field, 1 is excluded. Even if the convolution kernel with even size is padded symmetrically, the size of input feature map and output feature map cannot be kept unchanged. 2 is excluded. So we usually use 3 as the convolution kernel size. There are four common activation functions: sigmoid, tanh, relu and softplus. In this paper, we choose to use the relu activation function with faster convergence speed, so that after the first convolution, the image size becomes 200 * 200 * 32. Then, the dimension of the first convolution is reduced by pooling operation with step size of 2, and the core image with size of 100 * 100 * 32 is obtained, so the pooling result of the first convolution is obtained. However, due to too many parameters of the model, it will not only make the training time long, but also lead to the over fitting phenomenon of the model. Therefore, using dropout to make the activation value of a neuron stop working with a certain probability p can effectively alleviate the occurrence of over fitting and make the model more generalized.

The second convolution pooling is mainly based on the features extracted from the first convolution pooling, which may be some combined features. The size of the convolution core here is also 3 * 3, but the input is the result of the last convolution pooling, so the number of input channels is 32, and the number of output channels is 64. After the second convolution, the size of the core image becomes 100 * 100 * 64, and then through the pooling process with step size of 2, a core image with size of 50 * 50 * 64 is obtained, which completes the second convolution pooling.

The third convolution pooling is based on the second convolution, taking the second output as the input, repeating the operation of the second convolution, to get an output matrix. This output matrix is the matrix that can represent the image features through multiple convolutions.

The function of the full connection layer is to connect the feature matrix of the core image after the above three-layer convolution pooling, and send the output value to the classifier.

So far, the convolution neural network model is basically completed. Because the lithology recognition of core image is a classification problem, softmax is selected as the loss function. The next step is to put the samples into the constructed network for training to get a lithology recognition model.

4. Experimental results and analysis

In this paper, the core image samples prepared are divided into training sets and test sets according to the ratio of 8:2. The model is put into the model of core recognition which has been constructed. Through the process of image detection, the image region is continuously cut, the image feature values are extracted, and then self training is carried out, and the convergence effect is achieved. The accuracy rate reaches 90%, and the model is generated, The basic core image recognition requirements have been met.

The paper constructs the convolutional neural network model by machine learning, and constructs the lithological identification model of core image. Compared with the traditional method of extracting color and texture of core image and putting it into training device, it avoids the influence of different methods selection when extracting features, improves the effective extraction of key features and improves the accuracy of recognition.

5. Conclusions

This paper is to train a model that can identify the core lithology through the core image, so as to get rid of the low efficiency of manual identification of core lithology. At the same time, through the machine learning method, the problems encountered in the traditional core recognition method are solved, and the accuracy is improved. In the future, using machine learning and actual needs, we can build a more efficient and accurate model.

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