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Quantitative Identification of Sandstone Lithology Based On Thin-Section Micrographs Using the U-net and U-net++ Semantic Segmentation Network

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Abstract

Quantitative identification of sandstone microscopic images is an essential task for sandstone reservoir characterization. The widely-used classical Gazzi-Dickinson point-counting method can be subjective, inconsistent and time-consuming. Furthermore, by directly putting labeled microscopic images of all rock types into image recognition models for training, most previous studies did not address the petrographic principle of artificial identification. In this study, U-Net and U-Net++ semantic segmentation networks that incorporated the sandstone petrographic principle in quantitative identification of sandstone was introduced.

Automatic identification of sandstone microscopic images requires prior knowledge learned from the identified sandstones with similar compositions. First, hundreds of thin-sections of typical sandstone reservoirs were selected from several key petroleum basins in China. Second, one-to-one single and orthogonal polarized images were taken for them. Third, the annotation software was used to label the type of each skeleton grain, including quartz, feldspar, lithic fragment and pore. Finally, 480 sets of data, each of which includes single and orthogonal polarized images and their ".json" format annotation results, were obtained for training and testing of the U-Net model to quantitatively analyze sandstone microscopic images.

Within the 480 sets of data, 6798 sandstone skeleton grains, including 4542 quartzes, 796 feldspars, 1248 lithic fragments and 212 pores were labeled. The sandstone thin-section quantitative identification model trained by 392 data sets achieved a training accuracy of 96% with the intersection over union at 78% for quartz, and a training accuracy of 88% with the intersection over union at 56% for lithic fragments. The remaining 88 data sets were used for testing, and the accuracy was 87% with its intersection over union at 74% for quartz and a training accuracy of 77% with the intersection over union at 54% for lithic fragments. As a classic fully convolutional network that excels in processing medical images, the U-Net or U-Net++ semantic segmentation network has also performed very well in quantitative identification of sandstone microscopic images. After the proportion of each sandstone skeleton grain has been identified,

the simple subdivision descriptive petrographic classification of the sandstone was determined according to the classic Dickinson sandstone taxonomic criteria. In other words, most current deep learning algorithms classify sandstones at the bulk rock level, but this U-Net model has been extended to the mineral level for comprehensive identification. Our vision-based sandstone lithology identification model has not only improved the accuracy of artificial identification but also reduced the instability and subjectivity of the traditional manual processing and expert decision-making approach.

In the future, we plan to increase the number and coverage of labeled thin-section images to evaluate the impact on the accuracy and consistency of the U-Net or U-Net++ model, and to expand the approach to identify other terrigenous clastic rock. Furthermore, we hope to improve the capability of the model to identify grains, such as monocrystalline and polycrystalline quartz from "quartz", K-feldspar and plagioclase from "feldspar", and igneous, metamorphic and sedimentary lithic fragments from "lithic fragments".

Introduction

With the rapid improvement of microscope manufacturing and thin-section grinding technology, Sorby (1880) proposed petrography based on the optical characteristics of rock thin-sections under a polarizing microscope. In the following 100 years, the theory of petrography was gradually improved, which became the basic methods of geology and geoscience research, as well as the fundamental content of petroleum exploration and production. Originally proposed by Gazzi (1966) and Dickinson (1970), and systematically summarized by Ingersoll et al. (1984), the Gazzi-Dickinson point-counting method expanded the traditional qualitative petrology research into quantification.

Efficiently and accurately excavating the huge amount of geological information included in the large number of thin-sections in the petroleum exploration and production has been become a key topic and research trend. The traditional thin-section identification mainly focused on naked eye observations and descriptions, which can be subjective, inconsistent and time-consuming. However, the rapid development of image recognition provides a new possibility for the digital and intelligent identification of lithography based on microscopic thin-section images. With the help of image recognition, thin-section images have the potential to provide broader basic geological interpretation for petroleum field production, which can greatly improve data utilization and work efficiency, and even complete the development paradigm of petrography.

Clastic and carbonates rocks are the most significant reservoirs in petroleum exploration and production. Among them, clastic rocks are formed by denudation, transportation, deposition and diagenesis of mechanically broken clastic materials from source rocks. The material composition of clastic rocks is mainly composed of two parts: one is the terrigenous clastic materials and matrix; the other is the cement formed by solution precipitation in the stage of sedimentation and diagenesis. Therefore, clastic rocks have clearer petrological connotation and principle. Moreover, sandstones of clastic rocks as the widely distributed and high-quality reservoir, and owning the most prominent partical types and morphological characteristics, they have the greatest potential to initially solve the problem of quantitative intelligent identification of sedimentary rock thin-section micrographs.

Recently, there have been a large number of studies on intelligent identification of lithology based on thin-section micrographs, including deep learning approaches applied in particle segmentation (Li et al., 2017; Zhang, 2020), mineral identification (Xu and Zhou, 2018; Guo et al., 2020), petrographic classification (Patel and Chatterjee, 2016; Cheng et al., 2017; Su et al., 2020), grading analysis (Yuan et al., 2015; Cheng and Fan, 2018), porosity analysis (Borazjani et al., 2016; Dong et al., 2019), permeability prediction (Peng et al., 2016; Shi and Jian, 2018), etc. Comparing with traditional manual methods, they were more efficient and accurate. However, most studies did not address the petrographic principle of artificial identification. In this study, U-Net and U-Net++ semantic segmentation networks, which have performed very well in medical image recognition, incorporated the sandstone petrographic principle in quantitative identification of sandstone was introduced.

Feasibility and algorithm

Although deep learning, especially image recongnition, has made great progress with the great improvement of computing power and advanced algorithms, at present most research of intelligent recognition of sanstone thin-section microscopic images have simple and superficial classification. Micrographs of all sandstone types are simply put into image recognition models for training, ignoring the traditional sandstone petrologic principle of manual recognition. The research led by information scientists pays too much attention to the selection of the algorithm and its network structure, and lacks the feasibility analysis and logic design from the perspective of petrologic principle. Finally, it is not oriented to practical applications and lacks the source power of updating and iteration.

In petrography, the thin-section recognition is a method used to qualitatively or quantitatively observe and describe the structure, mineral composition association of rocks based on crystal optics and photomineralogy. According to the optical properties under the polarizing microscope, the characteristics of thin-sections can be divided into single polarized light, orthogonal polarized light and cone light. The single polarized light mainly provides the mineral morphology, cleavage, color, polychromatism and absorbency, edge and Baker line, rough surface and protrusion features. While orthogonal polarized light mainly povides extinction, interference color, ductility and double crystal of mineral features. Cone light (rarely used, especially for sandstone with simple composition) mainly characterizes the axial and optical properties of minerals. Sandstone is mainly composed of quartz, feldspar and lithic fragments which three have distinguishable optical features. Thin-section identification of sandstone is mainly based on the identification of mutual content of quartz, feldspar and lithic fragments. The combination of micrographs of sandstone, thin-sections under single and orthogonal polarization basically covers all the information required for thin-section identification of sandstone. Therefore, it is feasible to quantitatively identify sandstone lithology based on micrographs of sandstone thin-sections.

At the beginning, U-Net was mainly used in the segmentation of medical images. Later, a large part of the segmentation networks of medical images will take U-Net as the backbone of the network. U-Net inherits the idea of FCN, but U-Net is completely symmetric, and the decoder is enhanced by convolution, while FCN is simply upsampled. The advantage of U-Net is its ability to obtain image information at multiple scales. In the coding operation, five pooling layers are adopted, and the resolution is constantly reduced in the process of downsampling to obtain image information at different scales. The image information gradually transfers from the point, line and gradient information in the bottom layer to the outline and more abstract information in the top layer. The whole network has completed the feature extraction and combination from fine to coarse, so that U-Net can get more comprehensive information. Since the characteristics of thin-section micrographs of sandstone are very similar to medical images, both of which have small sample sets and large single images, it is necessary to capture global information and analyze detailed information. Therefore, this study uses U-Net and its improved U-Net++ network structure to conduct quantitative identification of sandstone lithology based on thin-section micrographs.

Images collecting and labeling

Image collecting and sample labeling are the basis of establishing the image recognition model and directly impacts the accuracy of image recognition.

In this paper, 5723 rock thin-section samples of 12 types have been collected for intelligent identification, with a total of 20456 micrographs, including 1221 micrographs of 412 sandstone samples, which are mainly from famous petroleum basins in China, such as Songliao Basin and Bohai Bay Basin.

Within the collected sample set of sandstone thin-section micrographs, each is composed of one-to-one corresponding single polarized and orthogonal polarized micrographs. In order to reduce the impact of different complexities of micrographs, because of different granularitis in different sandstone samples, we crop the micrographs under the principle of ensuring that the number of skeleton particles in a single micrograph remains about 20. Then, according to the single polarizing and orthogonal polarizing micrographs of one sample, the annotation software was used to label the type of each skeleton grain, including quartz, feldspar, lithic fragment and pore (Figure 1).

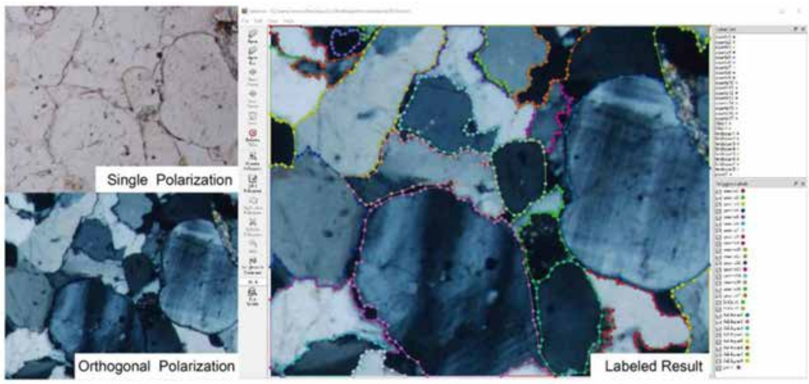

Figure 1—Annotation logic diagram of quality identification of sandstone thin-section images.

Finally, 480 sets of data, each of which includes single and orthogonal polarized images, and their ".json" format annotation results, were obtained for training and testing of the U-Net model to quantitatively analyze sandstone microscopic images. Within them, 6798 sandstone skeleton grains, including 4542 quartzes, 796 feldspars, 1248 lithic fragments and 212 pores were labeled.

Model training and testing

With the continuous expansion of the annotated sample set, this study conducted three rounds of model training and testing. In the first two rounds, the U-Net model was used and quartz was identified as the target. In the third model training and test, the improved U-Net++ model based on U-Net was adopted. Besides quartz, lithic fragments were also added to the identified target. The results of the three rounds of model training and testing (including accuracy, intersection over union, good and poor identification examples) are described below.

The first model training and testing

The first model training and testing was based on the U-Net semantic segmentation network. The dataset consisted of 2721 quartzes and their labels in 174 labeled sandstone thin-section micrographs. The training set consists of 128 labeled sandstone thin-section micrographs, and the testing set consists of 46 labeled sandstone thin-section micrographs. The training accuracy of the model is 87%, and the training intersection over union is 51%. The test accuracy rate was 76% and the test intersection over union was 64%. Examples of good and poor recognition are shown in Figure 2. The results of the first model training and testing were higher than expected, but it is necessary to adjust the model parameters and expand the dataset to improve the recognition accuracy and intersection over union.

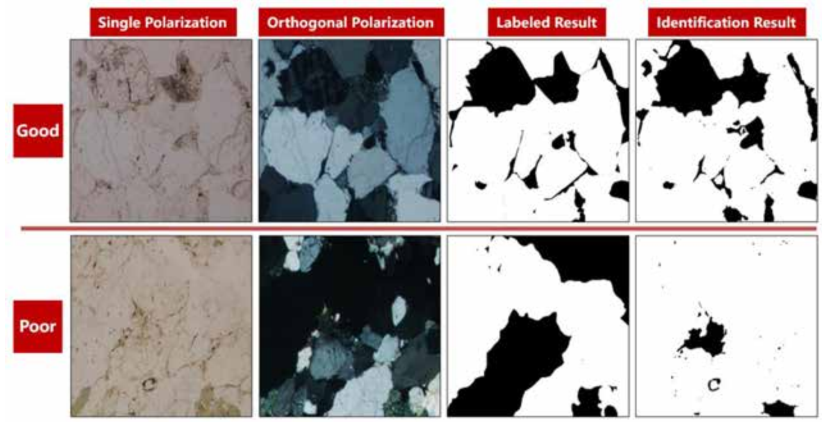

Figure 2—Good and poor identification results of some testing samples in the first model.

The second model training and testing

The second model training and testing was also based on the U-Net semantic segmentation network. While its dataset consisted of 3962 quartzes within 361 labeled sandstone thin-section micrograph. The training set consists of 302 labeled sandstone thin-section micrographs, and the testing set consists of 59 labeled sandstone thin-section micrographs. The training accuracy of the model is 96%, and the training intersection over union is 86%. The test accuracy rate was 86% and the test intersection over union was 65%. Examples of good and poor identification results are shown in Figure 3. The identification results of the second model training and testing were significantly better than those of the first, but there was a large gap between the testing and training intersection over union. Therefore, it was considered to change the model or adjust its parameters to improve the accuracy of recognition. Moreover, it is still necessary to expand the dataset to meet the requirements for image recognition of lithic fragments.

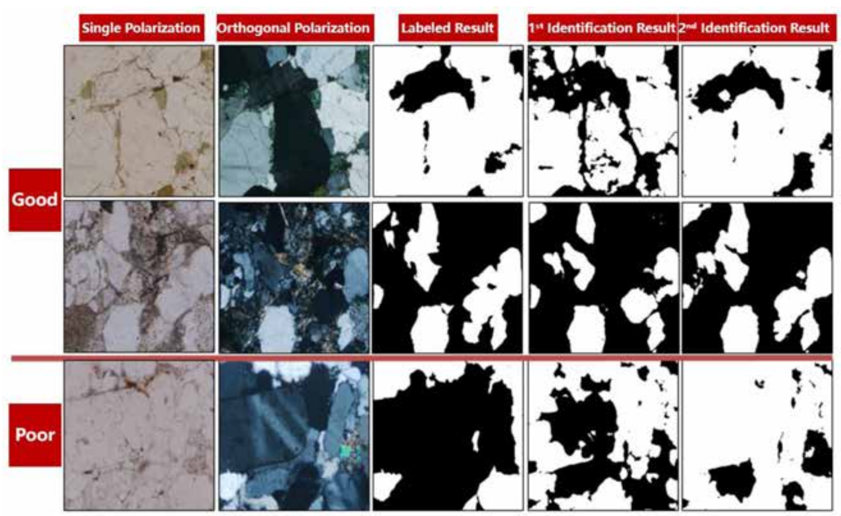

Figure 3—Good and poor identification results of the same testing samples in the first and second model.

The third model training and testing

In the third model training and testing, the U-Net model was replaced by the U-Net++ semantic segmentation network, and new data was added. The training set consisted of 4542 quartzes particles and their labels in 480 labeled sandstone thin-section micrographs. The training set consists of 392 labeled sandstone thin-section micrographs, and the testing set consists of 88 labeled sandstone thin-section micrographs. The training accuracy of the model is 96%, and the training intersection over union is 78%. The test accuracy rate was 87% and the test intersection over union was 74%. The quartz identified by this model are all good, as shown in Figure 4. Besides quartz, 200 images including 1249 labeled lithic fragments were filtrated. Also use the U-Net++ semantic segmentation network. The training accuracy of the model is 88%, and the training intersection over union is 59%. The test accuracy rate was 77% and the test intersection over union was 54%. Examples of good recognition are shown in Figure 5.

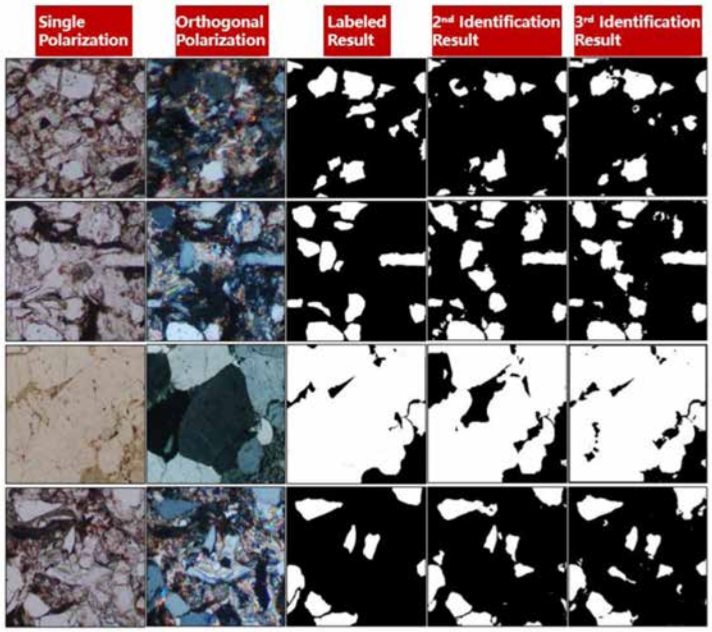

Figure 4—Good identification results of some testing quartzes in the second and third model.

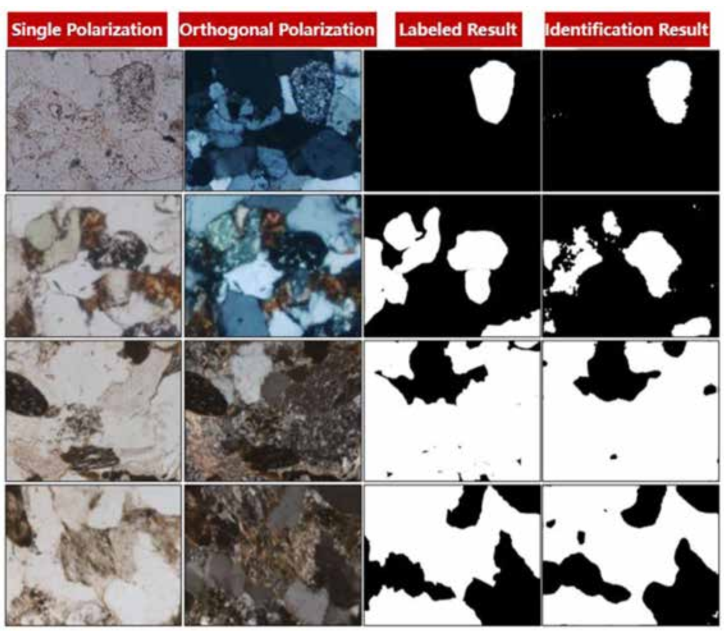

Figure 5—Good identification results of some testing lithic fragments in the second and third model.

Discussion

Table 1 and Figure 6 represent the variation rules of the accuracy and intersection over union of the three rounds of model training and testing. It can be observed that for image recognition of quartz, the identification accuracy and intersection over union of the model increased with the expansion of the dataset. When the improved U-Net++ semantic segmentation network based on the U-Net is adopted for the third model training and testing, the test intersection over union is significantly improved. In addition, unlike the second model whose training intersection over union is much higher than the test one, the training and test intersection over union in the third model are close, indicating that there is no overfitting in this modeling.

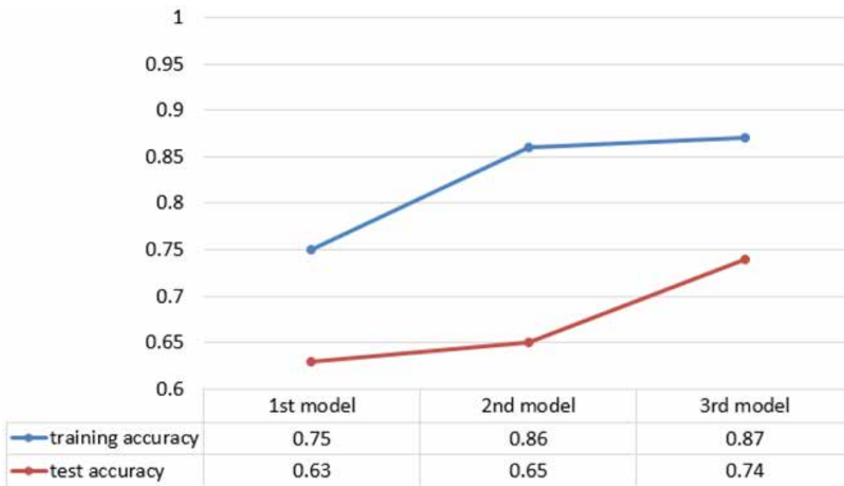

Figure 6—The variation rules of the accuracy and intersection over union of the three rounds of model training and testing.

Table 1—The accuracy and intersection over union of the three rounds of model training and testing and their identification target

Round No.		1st	2nd	3rd	
Identification target		Quartz	Quartz	Quartz	Lithic Fragment
Accuracy	training	87%	96%	96%	88%
	test	76%	86%	87%	77%
Intersection over Union	training	51%	86%	78%	59%
	test	64%	65%	74%	54%

It is worth noting that the U-Net++ network is more suitable for image recognition of a small sample. The U-Net++ model based on 1249 labled lithic fragments of 200 images has similar accuracy and intersection over union with the U-Net model based on 2721 labeled quartz of 171 images.

Due to the small amount of labeled feldspars, more labeled feldspars need to be added to meet the modeling of U-Net++ semantic segmentation network for feldspar recognition. However, the current identification results of quartz and lithic fragments make us believe that not only the identification accuracy and intersection ratio of quartz and intersection over union will continue to improve, but also the feldspar, which owns as the most obvious optical characteristics in sandstone debris. Finally, the goal of quantitative identification of sandstone lithology based on thin-section micrographs will be realized.

Implication

In petroleum exploration and production, the first part of the business that will be replaced by artificial intelligence will be the one with clear principle but needing mechanically repetitive work, such as image recognition of thin-sections. Therefore, the realization of image recognition of sandstone thin-sections is of great significance for petroleum exploration and production. It can overcome the subjectivity and instability of traditional expert manual identification, greatly improve the efficiency of quantitative identification of sandstone, and then lead the development of intelligent identification technology of rock thin-section to the breadth and accuracy.

In the future, we plan to increase the number and coverage of labeled thin-section images to evaluate the impact on the accuracy and consistency of the U-Net or U-Net++ model, and to expand the approach to identify other terrigenous clastic rock. Furthermore, we hope to improve the capability of the model to identify grains, such as monocrystalline and polycrystalline quartz from "quartz", K-feldspar and plagioclase from "feldspar", and igneous, metamorphic and sedimentary lithic fragments from "lithic fragments".

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