Accelerate fine-scale geological mapping with UAV and convolutional neural networks

Liang Zhan\textsuperscript{1,3,4}, Bin Liu\textsuperscript{1,3}, Xuejia Sang\textsuperscript{2,*} and Linfu Xue\textsuperscript{5}

\textsuperscript{1}Xinjiang Academy of Surveying &Mapping, Urumqi, China
\textsuperscript{2}School of Environment Science and Spatial Informatics, China University of Mining and Technology, Xuzhou, China
\textsuperscript{3}Engineering Research Center of Central Asia Geo-information Exploit and Utilize (M.N.R.), Urumqi, China
\textsuperscript{4}Academy of Geophysics, Chengdu University of Technology, Chengdu, China
\textsuperscript{5}College of Earth Science, Jilin University, Changchun 130061, China

*Corresponding author e-mail: sangxj@cumt.edu.cn

Abstract. We propose a new fine-scale mapping process, which UAV and CNNs to distinguish the rock mass. Studies have shown that with UAV high-resolution images, comparing with traditional classification methods (52.92\%~67.11\%), the CNNs method has a much higher classification accuracy rate (86.54\%). Although they can't completely replace ground work, UAV and CNNs, together with appropriate field geological survey work, can quickly fill fine-scale geological maps. This is significant for harsh areas.

1. Introduction

Taili is located in the southwestern part of Liaoning Province, northeast of the North China Craton. The composition and evolution of the rock in this area is complex, and it has undergone multiple periods of structural deformation and metamorphism and magma intrusion. The structural stage and structural features here are of great significance for revealing the tectonic evolution of the North China Craton [1]. But the research on the structural features of the Taili area is insufficient [2]. The main reason is the lack of fine-scale geological maps [3]. We can only observe the rock outcrops in about 3 hours at the time of the ebb, and it is almost impossible to draw fine-scale geological maps of this area using traditional methods. Therefore, we urgently need a way to quickly map to help researchers clarify the geological understanding of the Taili area.

Figure 1. A schematic map of location about Taili. There is a white line of parallel coastlines, which are stacked shells that indicate the position of the high tide.
Geological mapping is an important part of geological surveys. Remote Predictive Mapping (RPM) is a relatively fast and cost-effective method for generating geologic sketches [4]. RPM products can introduce geological work to more complex areas as geological sketches for regions that lack data, and improve the accuracy and consistency of mapping by combining machine learning ([5]-[7]).

2. Combine remote sensing images and ground work

It is impossible to determine the entire lithology by remote sensing images alone, ground surveying work is necessary. In order to facilitate the comparison of remote sensing images and actual conditions, we use Oruxmap Desktop software to package high-resolution remote sensing images acquired by UAV into map packages used by handheld devices. We use the digital mapping method to record the typical lithology of the ground as GeoPoints, which is convenient for selecting the lithology samples and the ROI required for classification in the GIS software.

Then, we identified seven land types and five typical lithologies in the study area. In order to get closer to the actual situation, this study did not remove non-geographic objects such as tourists and yachts that appeared in aerial photographs. We hope to increase the ability of the model to recognize “foreign objects” and improve the classification accuracy during the training of the classification model. Based on the ground conditions in the study area, this study determined the number of interpretations as 7. We selected a number of examples each type of landuse for various supervised classification algorithms.

3. CNNs Method

A CNNs network usually designed by a hierarchical structure, generally consists of 4 main neural network layers: input layer, convolution layers, pooling layers and fully-connected layers. Different layers play different roles.

The convolution layer is the core of CNNs. The convolution layer extracts the features contained in the image by convolution operations to the original image. The convolution layer is composed of a series of fixed size filters, known as convolution kernels, which are used to perform convolution operations on image data to produce feature maps [8]. The convolution kernels mainly implement convolution operation by the matrix multiplication operation to all RGB values in the original image. The formula is:
Here, $k$ represents the $k$th layer, $h$ represents the value of feature, $(i,j)$ represents the image’s location of $(i,j)$, $w^k$ represents the convolution kernel of the current layer, $b_k$ represents the bias. The parameters of the CNNs, such as the bias $b_k$ and convolution kernel, are usually trained in unsupervised ways [9].

We build a network (Figure 4) includes six weighted layers; the first four layers are convolutional layers, and the remaining three layers are fully connected layers. The output of the last full-connection layer is sent to a 7-way SoftMax layer, which produces a distribution that covers 7 types of labels. Our network maximizes the multi-class Logistic regression goal, which is equivalent to maximizing the logarithmic probability average of the correct labels in the training sample under the predicted distribution.

![Parametric schematic diagram of each layer about convolution neural network model](image)

**Figure 4.** Parametric schematic diagram of each layer about convolution neural network model

The Figure 5 describes in detail the CNNs method in the large-scale geological mapping process. In the figure, we generate high-resolution aerial photography images by UAV first, then we train convolutional neural network and classify the high-resolution image slices.

![Fine scale remote sensing interpretation workflow based on deep learning algorithm](image)

**Figure 5.** Fine scale remote sensing interpretation workflow based on deep learning algorithm.
4. Classification and result

In order to compare with the classification results of the existing classification methods, this paper also experimentally classifies and interprets the study area using the pixel classification based on the maximum likelihood method and the object-oriented classification based on the KNN method.

Figure 6. Identification results of three automated classification algorithms for study areas, (a) pixel-based classification, (b) object-oriented classification, (c) CNNs classification, (d) fine-scale geological map.

5. Conclusion

The effect of accelerating using the UAV and CNNs algorithms is obvious. UAV provides a platform for fast access to data where harsh. The CNNs algorithm accelerates the interpretation of high-resolution images and improves a lot of accuracy. We used the UAV and CNNs algorithms to accomplish the tasks that this traditional method could not accomplish, and drew a high-precision, fine-scale geological map. This will provide useful case for subsequent geological work.

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