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An intelligent system for mineral identification in thin sections based on a cascade approach

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ABSTRACT

In this study, an intelligent system for mineral identification in thin sections is proposed based on RGB and HSI color spaces and texture features in plane and cross polarized light. The proposed system has two phases for mineral identification. In phase#1, which is the segmentation phase, 12 color components are extracted for each pixel, and using an incremental clustering algorithm, several mineral clusters including index mineral are produced. Afterwards, in phase#2 which is the identification phase, the produced mineral clusters are identified based on a cascade classification approach. The first level of the cascade includes a set of artificial neural networks (ANNs) corresponding to the number of input minerals which are trained based on color components. In the first level, those minerals exhibiting different colors in plane or cross polarized light are identified. The second level of the cascade includes one ANN which is trained based on texture features in plane and cross polarized light images. In the second level, those minerals which are indistinguishable based on color components in both plane and cross polarized light are identified (are rejected in the first level of the cascade). The final output of the system is the name and number of minerals, boundary and percentage of each mineral in thin section, and eventually the name of probable target rock. The proposed system is able to recognize 23 test igneous minerals with the overall accuracy of 93.81%. The proposed system can be applied in important applications which require a real time segmentation and identification map such as petrography, and NASA Mars Explorations.

1. Introduction

An inherent part of modern geology is rock classification (Młynarczuk et al., 2013), and it is based on mineral identification. Rock classification plays an important role in mining engineering, rock mechanics, petrology, petrography, and many other branches of geosciences. Manual mineral identification, which is handled by a human expert in a mineralogy laboratory, can be conducted by such methods as polarized light microscopy, X-Ray Diffraction (XRD), X-Ray Fluorescence (XRF), Atomic Absorption Spectroscopy (AAS), Electron Micro Probe Analyzer (EMPA), Scanning Electron Microscopy-Energy Dispersive X-ray spectroscopy (SEM-EDX) and Transmission Electron Microscopy (TEM). The polarized light microscopy works based on thin sections and is a low cost, common and popular method for mineral identification, and also for conventional rock classification. However, manual mineral identification is a time consuming work, and also it is burdened with errors. Therefore, developing an intelligent method which is handled by a computer under a human expert supervision for mineral identification in thin sections is a great contribution in modern computational geology.

Thus far, several studies have been conducted to develop a method for minerals identification in thin sections (Marschallinger and Hofmann, 2010; Hofmann et al., 2013). In a study conducted by Fueten (1997), an automated system using rotated polarizer positions for automated analysis from rock thin sections is proposed. A classification algorithm was developed for identifying macroscopic scale minerals in desktop scanned rock samples in which 90.00% overall accuracy was obtained by using a maximum likelihood classifier (Marschallinger, 1997). In another study, thin section images in RGB and HSI color spaces were used, and 10 minerals were identified using

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an artificial neural network (ANN) with the overall accuracy of 93.53% (Thompson et al., 2001). In the experiment carried out by Ross et al. (2001), color and texture features were used as an input data to a genetic programming (GP) algorithm. In their study, 11 separate GPs were developed for all 11 minerals and the minerals were recognized with the overall accuracy in the range of 86.00–98.00%. Also, another GP was trained for identifying all 11 minerals; however, it failed to recognize them accurately. In another study, an algorithm for classifying the texture of ancient carbonates found in thin sections was suggested (Marmo et al., 2005). They used digital gray level images obtained from thin sections as an input data, and also used an ANN as the classification tool. As a result, they obtained an overall accuracy of 93.50% for correct recognition. A method based on albedo, color, texture, and shape properties for rock classification in natural scenes was presented by Dunlop (2006). Using a SVM (support vector machine) method, an overall accuracy of 86.30% was obtained for correct recognition. Image processing and mathematical morphology methods were used by MŁynarczuk (2010) for classifying rocks on the basis of their surface. In addition, a 6D feature space was used for clustering minerals, and as a result, five rocks were recognized with the overall accuracy of 95.00%. An approach to identify the texture of thin sections collected from different basalt rock samples was proposed in an experiment conducted by Singh et al. (2010). In their study, using an ANN the overall accuracy of 92.22% was obtained for identifying the texture of basalt rocks. An algorithm based on RGB and HSV color spaces was proposed by Baykan and Yılmaz (2010). As a result, five minerals were identified by using an ANN with the overall accuracy in the range of 81.00–98.00%. Another method was proposed by Młynarczuk et al. (2013) in which four color spaces including RGB, CIELab, YIQ, and HSV were used. They also used four pattern recognition methods including nearest neighbor, K-nearest neighbor, nearest mode, and optimal spherical neighborhoods. As a result, the best accuracy for identifying nine rock types was obtained by using CIElab color space and nearest neighbor classifier as high as 99.80%. Generally, there are two main limitations through the literature of the intelligent mineral identification. The first one is that using only color components or using both color and texture features at the same time for identifying all minerals. The second one is that mineral segmentation phase was not considered before mineral identification, and all pixels were fed to algorithms for identification at the same time. Accordingly, this approach reduced the efficiency of the intelligent mineral identification.

In order to cover these limitations, we have developed a reliable and robust intelligent system for mineral identification in thin sections. The developed system has two phases. Intelligent mineral segmentation is the phase#1 which was introduced in the first paper of our series of two papers (Izadi et al., 2015). In the phase#1, several mineral clusters including index minerals were produced as the segmented minerals. The phase#2, which is the focus of this study, is the intelligent mineral identification based on color components and texture features, and cascade classification approach. The cascade approach used in this study includes two levels. In the first level of the cascade, those mineral clusters that can be distinguished only by color components (labeled as group#1 in our database) are identified using a set of ANNs trained by color components (23 ANNs corresponding to the number of input minerals). In the second level of the cascade, those mineral clusters which cannot be distinguished only by color parameters (labeled as group#2 in our database) and are rejected from the first level of the cascade are identified using a set of ANN (one ANN) trained by textural features. For instance, we identify between minerals in the second level of the cascade. The proposed approach produces faster and more reliable results. The first contribution of the proposed system is using cascade classification approach, as the first time, and two sets of ANNs based on the color and textural features of minerals inside thin sections. The second contribution is extracting textural features in eight different directions including 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° based on three gray scales of 64, 128 and 256. The third contribution is developing a reliable intelligent system for minerals segmentation and identification in thin sections. The final output of the system is the name and number of minerals, boundaries and percentage of each mineral in thin section, and eventually the name of the probable target rock. We will show that both color and texture features are required for identifying some minerals (the group#2), not all minerals.

The rest of this paper is organized as follows. The database of images is described in Section 2. The details of the proposed system are presented in Section 3. Experimental results and discussion, and comparison are provided in Sections 5 and 6, respectively. Finally, in Section 6, the conclusion remarks are stated, and suggestions for further researches are provided.

2. Database collection

To establish a database for this study, the images were captured in both plane and cross polarized light in the maximum intensity of polarizing colors of the minerals (Ross et al., 2001), by using a digital camera installed on a polarized light microscopy. In our study, 135 thin sections consisting of a Glass and 22 common igneous minerals were collected (Table 1). All images were captured in RGB color space and TIFF file format, with the 5X magnification of the microscope objective, with size of 300 horizontal by 250 vertical pixels, and resolution of 96 dpi. The database was divided into two groups manually. The group#1 included those minerals which exhibit different colors in plane or cross polarized light. Therefore, color components are a perfect parameter for the identification of those minerals. The group#2 included those which exhibit almost the same color in plane and cross polarized light, and so, textural features are also required for correct identification.

Table 1
The list of minerals and Glass used in this study. Number of pixels indicates the total number of pixels of that mineral or Glass in all 135 thin sections.

Row#	Mineral	Group	Number of pixels	Row#	Mineral	Group	Number of pixels
1	Biotite	1	6975	**13**	Topaz	1	2500
2	Apatite	2	500	**14**	Kyanite	1	2500
3	Andalusite	2	500	**15**	Sanidine	2	1000
4	Muscovite	1	9980	**16**	Epidote	2	1500
5	Orthoclase	2	8500	**17**	Garnet	1	1000
6	Aegirine	1	3500	**18**	Nepheline	1	500
7	Quartz	2	15,795	**19**	Nosean	1	1000
8	Actinolite	1	2500	**20**	Hornblende	1	2000
9	Amphibole	1	500	**21**	Analcime	1	500
10	Olivine	2	3000	**22**	Augite	1	1000
11	Glass	1	5500	**23**	Hypersthene	1	1000
12	Talc	2	2500				