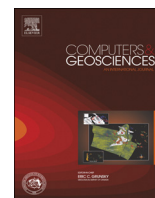




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The application of pattern recognition in the automatic classification of microscopic rock images



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ABSTRACT

The classification of rocks is an inherent part of modern geology. The manual identification of rock samples is a time-consuming process, and—due to the subjective nature of human judgement—burdened with risk. In the course of the study discussed in the present paper, the authors investigated the possibility of automating this process.

During the study, nine different rock samples were used. Their digital images were obtained from thin sections, with a polarizing microscope. These photographs were subsequently classified in an automatic manner, by means of four pattern recognition methods: the nearest neighbor algorithm, the K-nearest neighbor, the nearest mode algorithm, and the method of optimal spherical neighborhoods. The effectiveness of these methods was tested in four different color spaces: RGB, CIE Lab, YIQ, and HSV.

The results of the study show that the automatic recognition of the discussed rock types is possible. The study also revealed that, if the CIE Lab color space and the nearest neighbor classification method are used, the rock samples in question are classified correctly, with the recognition levels of 99.8%.

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1. Introduction

The development of the artificial intelligence makes it possible to automate more and more tasks, which, until now, have involved human judgement. This is due to the solutions provided by information technology.

Thus, the techniques involving pattern recognition and artificial intelligence are a fertile area for research as far as numerous scientific disciplines are concerned, and have already been applied in a lot of fields, such as astronomy (telescope resolution improvements and atmospheric degradation removal), life and behavioral sciences (anthropology, archeology, entomology, etc.), industrial applications (image controller machines, speech analysis, automated cytology, etc.), social and environmental applications (weather prediction, traffic analysis, urban growth determination (Friedman and Kandel, 1999)), medicine (computer-aided analysis and recognition of pathological wrist bone lesions (Ogiela et al., 2006), recognition of handwritten medical forms (Milewski et al., 2009)), agricultural applications (automatic recognition of fruit maturity (Jimenez et al., 1999)), geophysics (consistency analysis of geophysical datasets (Turlapaty et al., 2010), or continuous seismic monitoring of volcanoes (Messina and Langer, 2011)).

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So far, attempts to apply these methods in geological research have been considerably limited. In the study by Marschallinger (1997), polished rock samples were scanned by an image scanner. Then, the images were evaluated by means of multispectral image processing methods. The classification algorithm was tested for medium to coarse grained crystalline rocks. The Supervised Maximum Likelihood algorithm was the most robust approach, with recognition levels of approximately 90%. In the experiment by Baykan and Yilmaz (2010), the authors studied digital images obtained from the thin sections of igneous, metamorphic and sedimentary rocks. In the study, five common minerals were used. The three-layer feed forward network, which uses minimum square error correction, proved to be the most successful. Testing the neural network with previously unseen mineral samples yielded successful recognition results—as high as 81–98%. Another study, by Marmo et al. (2005), involved the analysis of 1000 photographs of the thin sections of ancient carbonates. As a result, a new methodology was developed. As the input, the methodology uses a 256 Gy-tone digital image; as the output, it yields a set of 23 values of numerical features obtained by image processing. This technique showed the accuracy of 93.3% and 93.5% in classifying the textures of carbonate rocks, with digitized images applied for 268 and 215 test sets, respectively. A new approach to identify the texture—based on image processing of thin sections of different basalt rock samples—was proposed in an experiment conducted by Singh et al. (2010). For each of the 300 different thin sections, 27 numerical parameters were measured, which were used to train

the multilayer perceptron of a neural network. In order to test the methodology, 90 images (30 in each section) from thin sections of different areas were used. The methodology showed an accuracy of 92.22% in the automatic identification of the basaltic rocks textures. Młynarczyk (2010) used image processing and mathematical morphology methods to classify rocks on the basis of their surface. He used the data obtained from a laser profilometer, and proposed methods of classification based on the analysis of the 6D feature space, which revealed correct classifications of 5 investigated rocks with an accuracy of up to 95%. The pattern recognition methodology for constructing an expert system for petrography and mechanical analysis of rocks was presented in a paper by Bodziony et al. (2003), where the authors discussed the use of tree automata and efficient ETPL(k) graph automata for pattern recognition, as well as pointed out the great accuracy of the presented methods. In the work by Peterzell and Kruhl (2009), the possibility of the accurate quantification of automatically digitized mineral-phase distribution patterns in igneous rocks was analyzed. Ghiasi-Freez et al. (2012) introduced a model for semi-automatic identification of porosity types within thin section images, having applied a pattern recognition algorithm to this end. Ishikawa and Gulick (2013) presented a robust and autonomous mineral classifier for analyzing igneous rocks. This study shows that machine learning methods, specifically artificial neural networks, can be trained using spectral data acquired by in situ Raman spectroscopy in order to accurately distinguish among key minerals for characterizing the composition of igneous rocks. These minerals include olivine, quartz, plagioclase, potassium feldspar, mica, and several pyroxenes. On average, the accuracy rate for this classifier was 83%. In the study by Dunlop (2006) the author presents a very interesting study on the automatic detection and classification of rocks in natural scenes. Such a study may find application in automated analysis inaccessible to human environments, such as the surface of another planet or the ocean floor. Work was focused more on the detection of rock rather than on the classification process but the author has managed to achieve a satisfactory result at the level of correct classification of 86.3%.

The aim of the research presented in this paper was to examine the possibility of developing an algorithm based on the standard methods of pattern recognition, which allows the automatic classification of the large collection of microscopic images of rocks. Such classification, based on the essential parameters of digital images, is important from the point of view of the analysis of microscopic image databases.

2. Materials and methods

2.1. The rocks

Nine rocks were used in this study. The selected rocks revealed different spectrographic features, as well as different physical and mechanical properties. Thin sections of the rocks were used. The camera, which was integrated with the microscope, registered digital photographs saved in the TIFF format. Depending on the analyzing rock microscope magnification was set to 50x or 100x. The illumination was arranged optimally (to avoid over- and under-exposure) and was never changed during the acquisition of images of the given thin section. For each rock type, the photos were taken of at least three thin sections. We took 300 pictures of each rock type. As a result, the total of 2700 color images were registered for 9 rocks. The resolution of the images was 1280 × 960 pixels. The images were registered for the following rocks:

1. Dolomite from Laskowa Gora (the Swietokrzyskie Mountains, south-central Poland)—a Devonian sedimentary, monomineral

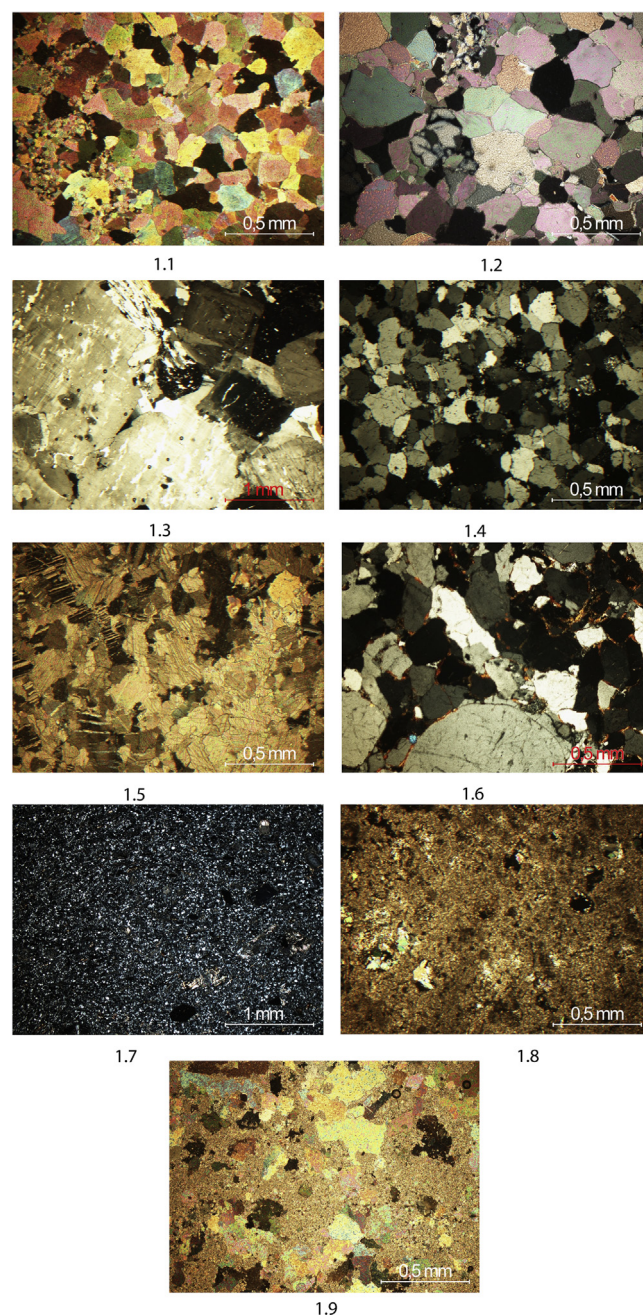


Fig. 1. The samples of the microscopic images of selected rocks (1.1. Dolomite from Laskowa Gora, 100x; 1.2 Dolomite from Redziny, 100x; 1.3 Granite from Strzelin, 50x; 1.4 Quartzite from Wisniowka, 100x; 1.5 Biala Marianna Marble, 100x; 1.6 Sandstone from Tumlin, 100x; 1.7 Porphyry from Miekinia, 50x; 1.8 Limestone from Buszewo, 100x; 1.9 Limestone from Czatkowice, 100x).

rock made entirely of dolomite crystals of the size of 0.2–0.6 mm, connected along straight lines or, in rare cases, along tooth-shaped lines (Fig. 1.1).

2. Dolomite from Redziny (the Sudety Mountains, south-western Poland), a lower-carbon metamorphic, monomineral rock with equal crystals made entirely of dolomite crystals of the size of 0.1–0.3 mm. The grain borderlines are mostly equal, sometimes tooth-shaped, with no binder (Fig. 1.2).
3. Granite from Strzelin (Silesian Lowlands, south-western Poland), an igneous rock of a holocrystalline structure, built of feldspar, quartz, and biotite. Feldspars are represented by a variety of alkaline rocks and plagioclases. Quartz creates grains of the size of 0.4–2.0 mm. When the macroscopic scale of

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