On the Texture and Spectral Reflectance Analysis of Main Rock-Forming Minerals

Krezhova D.D.[1], Pristavova S.D.[2], Tsaneva M.G.[3], Yanev T.K.[1]

[1]Solar-Terrestrial Influences Institute, Bulgarian Academy of Sciences, Sofia, Bulgaria, dkrezhova@stil.bas.bg
[2]University of Mining and Geology, "St. Ivan Rilski", Sofia, Bulgaria
[3] Medical University, Pleven, Bulgaria

Texture and spectral reflectance analysis were applied for identification and discrimination of the main rock-forming minerals of the rocks. Two representatives of magmatic and metamorphic rocks - amphibole gabbro and kyanite schist that have wide occurrence on the territory of Bulgaria were investigated. Gabbro is a main element of the Struma Diorite Complex while the kyanite schists are cropping out in the region of the village of Lebnitsa, Blagoevgrad district. We used gray-level co-occurrence matrices (GLCM) to quantitatively evaluate texture features and to determine which of them are best for mineral identification. Five texture features (angular second moment, contrast, correlation, inverse difference moment and entropy) were computed by the image processing and analysis program ImageJ and by the plugin GLCM Texture. Spectral signatures were obtained from optical reflectance measurement taken with a multichannel spectrometer in the region between 480 and 810 nm. By means of the Student's t-criterion and discriminant analysis statistically significant differences between the texture features of the main rock minerals were found for contrast and correlation in the case of gabbro and contrast and inverse difference moment for kyanite schist. For the spectral reflectance characteristics, t-criterion was applied in eight wavelengths disposed equidistantly over the spectral range investigated and statistically significant differences were established in seven of them for the two rocks examined. The results show that a combination of spectral and texture analysis may provide a robust method of discrimination with potential for application in real time.

Introduction

Techniques for the processing and interpretation of remotely sensed data have been widely used for various applications relating to surface and near surface environments (especially forest, crops, surface geological features, and oceans) [1, 2]. With the development of high techniques, large amounts of data are obtained by different types of sensors. Nowadays, an increasing quantity of multi-source remote sensing data acquired from many geographical areas is available. To investigate these data, there is a need to develop effective data processing techniques in order to take the advantage of such multi-source characteristics. In particular, in the context of classification problems, by combining more data features an improvement of accuracy could be achieved, which may be of important significance in real applications. In general, the spectral and texture information of multi-source remote sensing plays an important role in the classification process [3-5].

Image texture analysis is useful as a spectral image analysis tool because texture is independent of image tone. Texture can be defined as a variation of the pixel intensities in image sub-regions. The texture feature describes the attribution between a pixel and the other pixels around it. Texture features represent the spatial information of an image, which can be regarded as an important visual primitive to search visually similar patterns in the image [6]. The extraction of texture features from high resolution remote sensing imagery provides a complementary source of data for those applications in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous landscape units [7].

However, there is a wide range of texture analyses that are used with different criteria for feature extraction: statistical methods (grey level co-occurrence matrix - GLCM, semivariogram analysis); filter techniques (energy filters, Gabor filters), or the most recent techniques based on wavelet decomposition. The combination of parameters that optimize a method for a specific application should be decided when these techniques are used [8, 9].

Among all texture analysis methods, the Grey Level Co-occurrence Matrix (GLCM) is one of the most widely used techniques in remote sensing and has been proven amongst the most powerful methods for many situations of texture classification [10]. The GLCM was first used by Julesz [11] and proposed by Haralick et al [12] as an approach to extracting textural features for image classification purposes. The method is based on the assumption that grey tones are spatially dependant (conditional joint probabilities) and that their dependency can be expressed through a co-occurrence matrix. Haralick et al [12] have therefore proposed a series of measurements taken from such matrices that relate to various aspects of texture (i.e. homogeneity, contrast, entropy, etc.).

The texture is an important surface characteristic, which can be used to identify and recognize the main rock-forming minerals or components. The optical properties of rocks (spectral reflectance) depend on a complex interaction of factors including rock chemistry, modal composition, texture, and crystallinity [13].

The aim of the present paper is to assess the applicability of texture and spectral reflectance analysis as complementary tools for discrimination of the main rock-forming minerals using high resolution data and to evaluate which of the studied texture features are best for mineral identification.

Materials and methods

Petrographic characteristic of the rock specimens

The specimen of amphibole gabbro, Fig. 1, is igneous basic intrusive rock. It is medium to coarse grained with massive texture. The investigated surface contains contrast by colour minerals - amphibole (dark green) and basic plagioclase (whitish - gray) in quantity relation approximately 2:1. The mineral composition of the gabbro includes also, clinopyroxene, sphene, apatite and ore minerals. These rocks have widely occurrence on the territory of the Western Bulgaria and they are main element of the Struma Diorite Complex.

The specimen of kyanite schist (metapellite), Fig. 2, is fine up to medium grained, greyish-brownish-reddish of colour, with a fine schistose structure. By origin, it is a regional metamorphic rock - an amphibolite's facieses of metamorphism. It is build up of porphyroblasts of greyish blue kyanite and reddish brown garnet amid a fine grained crystalline mass of biotite, sericite and quartz. The texture of this rock specimen is lepidogranoblastic and porphyroblastic by kyanite and garnet.

Fig. 1. Specimen of amphibole gabbro

Fig. 2. Specimen of kyanite schist

A large portion of the kyanite porphiroblasts is substituted by cryptocrystalline aggregates of sericite, which macroscopically is reflected by the change in colour - from grey-bluish to grey-whitish. The brown-reddish tint of the rock as a whole comes out of the abundant presence of biotite (brown red) and garnet (reddish brown). The rock exhibits a strong mineral linearity by the mineral kyanite. The kyanite schists are cropping out in the region of the village of Lebnitsa, Blagoevgrad district. The studied rocks are characteristic component of the Gneiss-migmatite Complex - Maleshevska Group (Ograzhden block, Vlahina block, and south-western part of the West Rila block).

Texture evaluations

The texture of the rock specimens was examined from the analysis of their digital images with high resolution. The images were taken with a digital camera CANON SX100IS with a CCD colour sensor containing about 8.3 Megapixels. The lens is a zoom-type 6-60 mm / f 2.8–4.3 optical system.

We used the co-occurrence method introduced by Haralick [12]. Gray level co-occurrence matrix is a second order statistical tool useful to characterize texture features. It considers the contemporary occurrences of gray levels in corresponding displaced positions of the original image. GLCMs are typically computed for a number of different offsets unless a priori information is available about the underlying texture.

By twenty areas of the images with different size of each one mineral group of the two rocks were separated. The co-occurrence matrix of these regions was computed and texture analysis was performed by these matrices. Five of the most popular features: Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM) and Entropy were computed by the image processing and analysis program ImageJ [14] and by the plugin GLCM Texture [15] and analysed by statistical methods.

The definitions of the GLCM texture features used as referenced in this research are given in Table I.

TABLE I
GLCM texture features

Texture feature	Definition
ASM	$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij}^2$
Contrast	$Contrast = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 \; p_{ij}$
Correlation	$Correlation = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)}{\sqrt{\sigma_x \sigma_y}} \, p_{ij}$
IDM	$IDM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2}$
Entropy	$Entropy = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij} \log p_{ij}$

ASM measures homogeneity of the image, and with regularity of the texture it increases. Contrast (sum of squares variance) measures the local variations in the gray-level co-occurrence matrix. Correlation measures the joint probability occurrence of the specified pixel pairs. Homogeneity IDM measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Entropy measures the irregularity (variety) of the texture, and increases with variety.

Spectral reflectance

The spectral reflectance of the rocks was collected using a multichannel spectrometer [16] in the visible and near infrared ranges (480÷810 nm) of the spectrum in 128 wavebands at a spectral resolution of 2.6 nm and a spatial resolution of 2 mm^2 for the actual distance of 2.5 m between the specimens and the focal plane of the spectrometer.

The spectrometric measurements of each rock specimen were performed in contiguous areas (pixels) along a line on the surface preceded by records of dark current and of diffusely scattered radiation from the standard white screen. For determination of the spectral reflectance characteristic (SRC) the spectral data recorded undergo a subsequent treatment. It includes averaging of the spectra of each one pixel and of the standard screen data, and accounting for the dark current. For each average SRC the values of spectral reflectance (in relative units) at the 128 wavelengths were determined.

Statistical methods

To establish the statistical significance of the mean differences between texture features and SRC of different groups of minerals we applied discriminant analysis (DA) and Student's t-criterion. The DA gives the option to discriminate between the texture features of the groups of minerals by juxtaposing a statistical probability to every one outcome obtained. The Student t-criterion was applied as well over the set of five texture features to establish the statistical significance of the mean differences.

The t-criterion was applied also over the set of SRC of rock mineral components at eight wavelengths chosen to be disposed uniformly over the range including the green, red and the near infrared bands (λ_1 = 480 nm, λ_2 = 500.8 nm, λ_3 = 550.2 nm, λ_4 = 599.6 nm, λ_5 = 649 nm, λ_6 = 701 nm, λ_7 = 750.4 nm, and λ_8 = 779 nm).

Results and Discussion

Fig. 3 shows SRC of the investigated areas of the specimen gabbro. Two sub-classes were discriminated corresponding to the two main rock-forming minerals - amphibole (dark red) and basic plagioclase (blue). In Fig. 4 are shown four of the areas used for texture analysis of two mineral groups of gabbro: a) plagioclase (whitish gray) and b) amphibole (dark green), Fig. 1. Fig. 5 shows the SRC of the examined areas of the specimen kyanite schist. Two groups are clearly discriminated also corresponding to the rock-forming minerals - kyanite porphiroblasts (grey curves) and biotite and garnet (blue curves) [17].

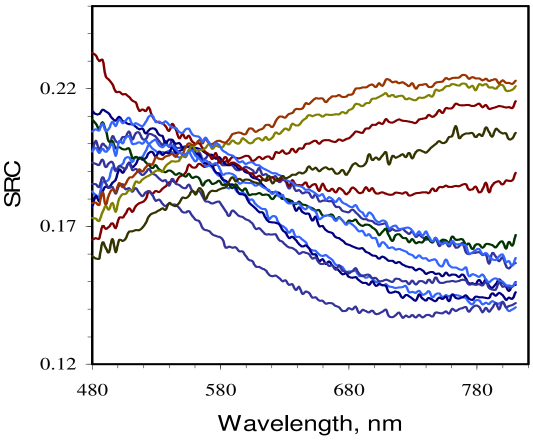

Fig. 3. SRC of specimen amphibole gabbro

In Fig. 6 we show four areas used for texture analysis on surface of kyanite schist: a) kyanite porphiroblasts (from grey-bluish to grey-whitish) and b) biotite and garnet (reddish brown).

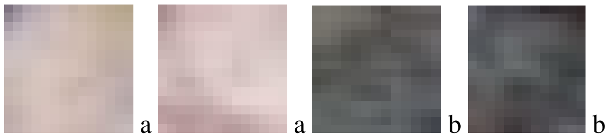

Fig. 4. Areas of two main mineral groups of gabbro – plagioclase a) and amphibole b)

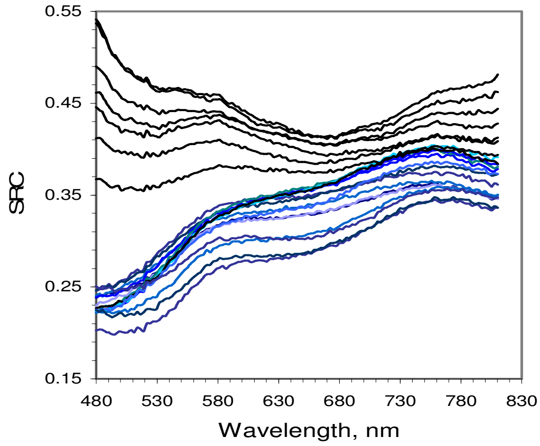

Fig. 5. SRC of specimen kyanite schist

The results of the statistical data processing of the five texture features of the two main mineral groups containing the gabbro and kyanite schist through the linear discriminant analysis are set out in Table II, where p_{DA} is the significance level of the null hypothesis.

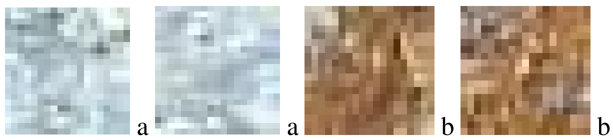

Fig. 6. Areas of two main mineral groups kyanite schist: a) kyanite porphiroblasts and b) biotite

TABLE II
Significance level p of the results obtained through DA model for the texture features

Spaces of texture features gabbro	p_{DA}	Spaces of texture features kyanite sc	p_{DA}
1	0.92	1	0.618
2	<0.000	2	<0.000
3	<0.000	3	0.137
4	0.989	4	<0.001
5	0.287	5	0.464
1/4	0.991	1/3	0.757
1/5	0.011	1/5	0.757
4/5	0.494	3/5	0.306
1/4/5	0.010	1/3/5	0.51
1 to/5	<0.000	1 to5	<0.000

The results are statistically significant if $p < 0.05$. As it is seen, the main mineral components are distinguished significantly separately (one dimensional space) by the features contrast and correlation in the case of gabbro and contrast and IDM for kyanite schist. Satisfactory good classification of the main minerals of gabbro was obtained in the two and three dimensional spaces defined by the rest features (ASM, entropy) and (ASM, entropy, IDM).

In Table II and Table III the numbers' meaning is as follows: 1 - ASM; 2 – Contrast; 3 – Correlation; 4 – IDM; 5 – Entropy.

The t-criterion was applied over the set of texture features (Table III). For kyanite schist no satisfactory discrimination was observed in the two dimensional spaces formed by ASM, entropy and correlation.

In the five dimensional space formed by all texture features a full discrimination was observed. The t-criterion was applied over a set of the SRC of the mineral classes for two rock specimens. Statistically significant differences were revealed for spectral data for all investigated wavelengths with the exception of λ_4 for kyanite schist and λ_4 and λ_5 for gabbro.

TABLE III
Significance level p of the results obtained through t-criterion for the texture features

Texture features	p_t gabbro	p_t kyan. schist
1	0.919	0.516
2	<0.000	<0.000
3	<0.000	0.049
4	0.985	<0.000
5	0.287	0.334

Conclusions

The comparison between the results for the discriminative possibilities of texture features obtained through linear DA and Student t-criterion gives similar results. It was found that the contrast gives the best results in a single feature space. The results show that co-occurrence matrix approach is also an effective method for discrimination of the main rock-forming minerals. The combination of spectral and texture analysis may provide a robust method of discrimination with potential for real time application.

The spectral properties of magmatic and metamorphic rocks depend on a complex interaction of factors including the efects due to mineral grain size, arrangement and close packing, the spectral behavior of the intergranular materials in rocks and etc. Texture afects the spectral properties of the rocks in a still not fully understood way. The correlation of rock spectrometric parameters with different compositional variables can give insights into the magma-rock dynamic system evolution, not only providing information on the rock composition, but also on the geologic context of the rock formation.

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