Classification of Intrusive Igneous Rocks Using Digital Image Processing: A Binary Approach

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Abstract: *One of the methods used to classify intrusive igneous rocks is by observing the intensity of light- and dark- coloured mineral. However, this method is normally based on perception, i.e., the outcome might be inconsistent across different observers. In this study, the coloured digital image of intrusive igneous rock is converted to a binary image and the percentages of black pixels are calculated. The results show that the biotite granite, which is felsic and light-coloured rock, contained the least amount of dark minerals, whereas peridotite, the ultramafic igneous rock (dark-coloured) contained the highest percentage of dark minerals, which is more than 60%.*

Keywords: Intrusive igneous rocks, pixel intensity, rocks mineral, binary image, black pixels

1. INTRODUCTION

Rock is one of the most abundant materials on earth. This is due to the fact that rocks originated from magma, the fluid that constitutes the earth. Geologists classify rocks into three categories: igneous, sedimentary and metamorphic rocks. The rocks that directly originated from magma are igneous rocks and can be found abundantly on earth surface.

Geologists classify igneous rocks into four main groups, namely felsic (acid), intermediate, mafic (basic) and ultramafic. Their differences are due to different amount of substances or minerals consisted in each type of rocks. Felsic rock gets its name due to presence of a large amount of feldspar and silica. Granite is a common felsic rock. Another group, mafic rocks, consists of high amount of magnesium and iron. Basalt is a common mafic rock. If the magnesium and iron is quite high, the rock is grouped as ultramafic. An ultramafic rock such as perioditite is abundantly found in mantle but rarely in the crust. Another group, which is intermediate rocks, contains the amount of substances or minerals similar to felsic and mafic rocks. The most common intermediate rock is andesite.

As the content of dark minerals in a rock increases, its colour turns darker. Felsic rock contains less dark minerals, while other types of rock contain more. As the type of rock varies from intermediate to mafic and ultramafic, the amount of dark minerals increases.[1] Figure 1 shows the names of common igneous rocks based on the minerals and texture of rocks.[2]

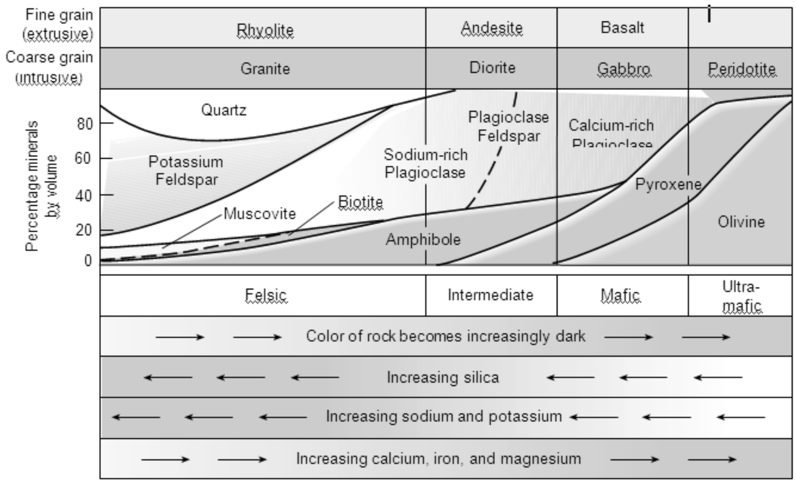


Figure 1: The names of common igneous rocks based on the minerals and texture.[2]

Currently, in order to differentiate between these four groups of rock, one may carry out observation with naked eyes or by using magnifying glass. Another method is via petrographic study, where the rock is cut and viewed under microscope. Mineral identity, chemical composition and structural state, and growth of strain are often obtained by petrography study. Since both are done manually, these processes are more inclined towards qualitative analysis rather than quantitative, as individual observations may vary.[3] This could possibly lead to misclassification by the observer. Furthermore, for petrographic study, the rocks need to be cut into thin slices and viewed under polarising minerals. Therefore, it is necessary to find a more consistent, accurate and rapid method to classify the igneous rocks into the correct group. This paper tries to propose a new method of classifying igneous rocks using digital image processing technique. This will be achieved by determining the black pixels of the binary images, which represent the dark minerals of the rocks.

1.1 Minerals of Igneous Rocks

Felsic and mafic rock usually refer to the distribution of coloured-minerals in the rocks, where the minerals themselves are identified as the genesis of igneous rocks. Felsic minerals usually represent light-coloured minerals whereas the dark-coloured minerals represent the mafic minerals. Felsic minerals include quartz, muscovite, feldspars and feldspathoids, whereas mafic minerals contain olivines, pyroxenes, amphiboles and biotite.

The colour index of a rock is an expression of the percentage of mafic minerals it contains. Four categories have been distinguished: (1) leucocratic rocks, which contain less than 30% dark minerals, i.e., acidic or felsic rocks, (2) mesocratic rocks, which contain 30–60% dark minerals, (3) melanocratic rocks, which contain 60–90% dark minerals, i.e., basic rocks or mafic, and (4) hypermelanic rocks, which contain over 90% dark minerals, i.e., ultrabasic or ultramafic rocks.[1]

1.2 Applications of Digital Image Processing in Civil Engineering

Digital image processing has been applied widely in science and engineering, as the advancement of technology in manipulating and processing images continues. In civil engineering, digital image processing had been employed particularly in geotechnical engineering such as pores-solid soil analysis,[4] flow in porous media,[5] sediment grain size analysis,[6] measurement of horizontal soil shrinkage,[7] constituents of soil,[8] mesostructure of soil-rock mixture,[9] surface fractal dimension of the soil-pore interface,[10] measurement of in-plane displacements in soil testing[11] and analysis of particle size distribution of coarse aggregate.[12] It was also applied in material engineering such as in morphology of cement and concrete.[13] As for mineral identification, several processing techniques, such as colour analysis, textural analysis and frequency domain analysis are studied extensively using quantitative method.[3,14]

2. EXPERIMENTAL

There are several methods that had been developed to identify minerals using digital image processing. Colour analysis is one of them. The method uses Red Blue Green (RGB) and HIS colour model to study the optical characteristic and physical phenomena of minerals.[3] Assessment is also made on the characteristic of interference colour in rock forming mineral images from a thin section of image under polarising microscope through video camera throughout a frame grabber card during cross-nicol observation.[14] Identification of carbonaceous materials or oxidised iron is done by computing the mean and variance or in the form of histograms of the distribution of colour or intensity over the rock by using RGB, Hue Saturation Value (HSV) and CIE L*a*b*CIELAB.[15,16]

2.1 Image Acquisition

For this set of experiments, a total of 20 samples of common intrusive igneous rocks, i.e., biotite granite, diorite, gabbro, peridotite and syenite are used from four different boxes. The sources are from Ward's Natural Science reference set.

The experiment was conducted in the Geology Laboratory, Faculty of Civil Engineering, Universiti Teknologi Mara Pulau Pinang, Malaysia. The images were captured using Logitech HD Pro Webcam C910 and stored in the laptop computer for further analysis. The rocks were placed on the visualiser at different zoom settings. A fairly diffused lighting set up was used. For image capturing, the arrangement of the specimen and image-capturing device is shown in Figure 2. The captured images with 1024 × 721 resolutions were converted to binary images. A binary image is an image that consists of only black (intensity = 0) and white (intensity = 1) pixel colours. These pixel colours depend on the black intensity and threshold value of that image. If the intensity is larger than threshold value, the pixel colour is white and vice versa. In this experiment, the threshold value was set to a default value, which is 0.5. The percentage of black pixels is determined using Equation 1:

$$\text{Percentage of black pixels } (\%) = \frac{\text{Amount of black pixels}}{\text{Amount of overall pixels}} \times 100\% \qquad (1)$$

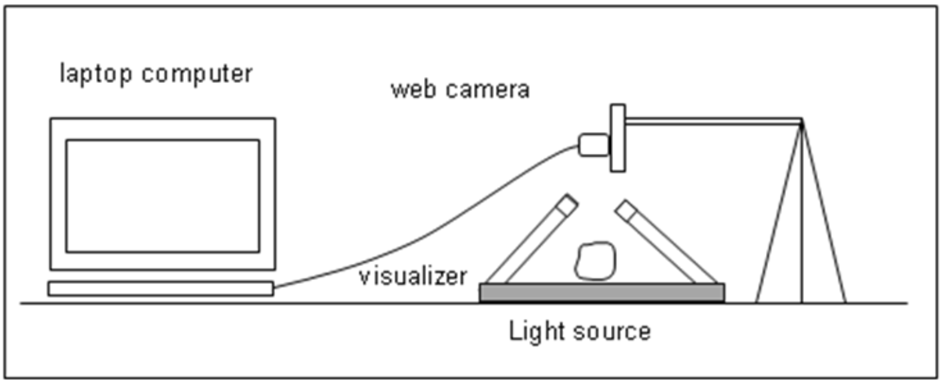


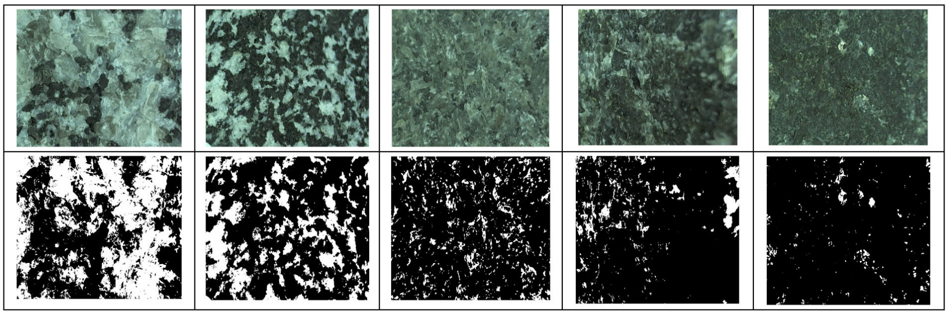
Figure 2: Schematic diagram showing the arrangement of image-capturing process.

3. RESULTS AND DISCUSSION

3.1 Image Analysis

The images were captured for 5 common intrusive igneous rocks from 4 different box samples, making the total to be 20. The images were captured from 3 to 4 clear sides of the rocks, i.e., a) left side, b) right side, c) broad part with number and d) back side of broad par. The rocks were labelled accordingly. For example, Granite_1_A refers to granite-type rock, with the number 1 referring to box 1 and A for image captured from left side of the rock.

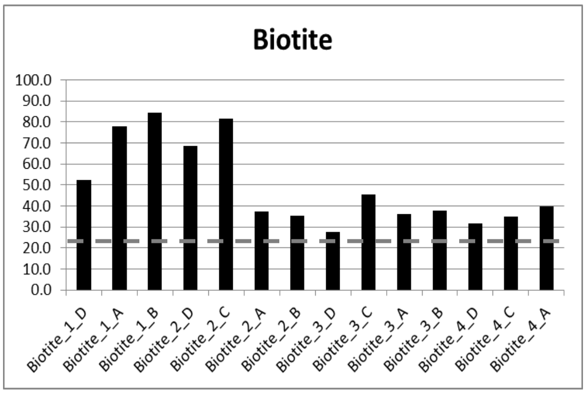
The captured images were converted into binary images. Some of the images were not used in the analysis due to blurring and clarity issue, which affected pixel calculation. Figure 3 shows the actual images and binary images for biotite granite, diorite, syenite, gabbro and peridotite respectively.



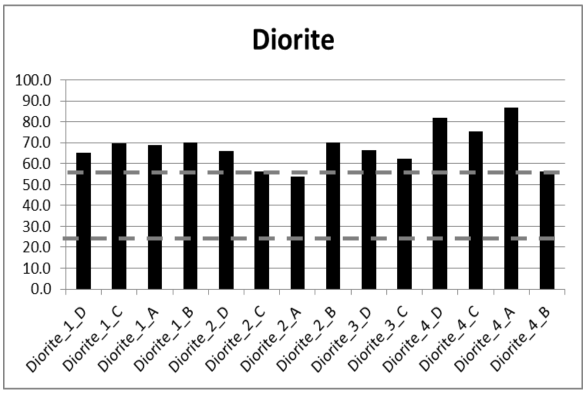
(a) (b) (c) (d) (e)

Figure 3: Actual images (above) and binary images (below) of: (a) biotite granite, (b) diorite, (c) syenite, (d) gabbro and (e) peridotite.

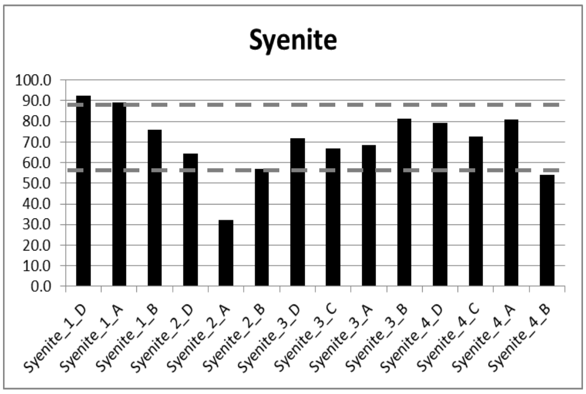
The results from the image conversion were tabulated into a graph in order to determine the average black pixels obtained from the rocks. Figure 4 shows the tabulation.



(a)

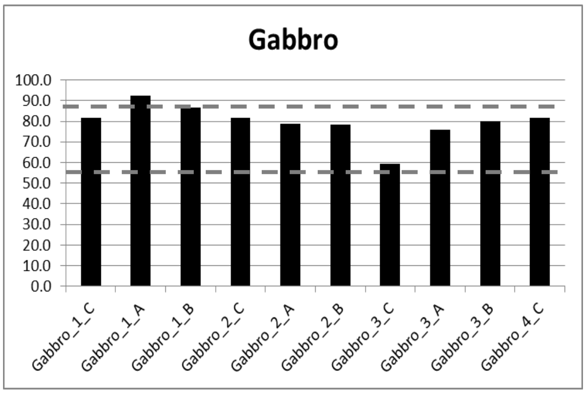


(b)

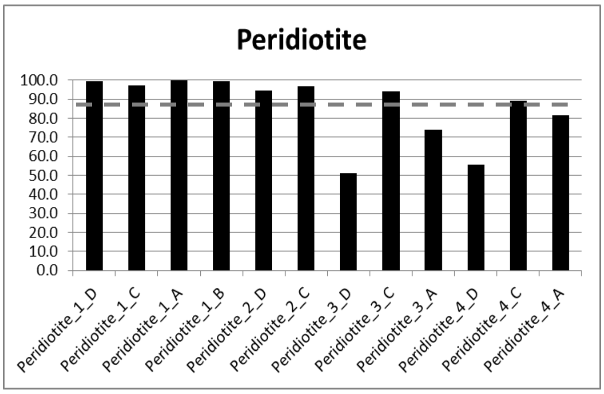


(c)

Figure 4: Percentage of black pixels in: (a) biotite granite, (b) diorite, (c) syenite, (d) gabbro and (e) peridotite.



(d)



(e)

Figure 4: Percentage of black pixels in: (a) biotite granite, (b) diorite, (c) syenite, (d) gabbro and (e) peridotite. (continued)

3.2 RESULTS AND DISCUSSION

3.2.1 Image Analysis

From Figure 3, it can be seen that biotite granite has the lowest percentage of black pixels, while peridotite has the highest. The images have been arranged in order of the increasing percentage of black pixels obtained, reflecting that the colour of rock becomes increasingly dark.[2]

From Figure 4, biotite granite shows the lowest percentage of black pixels, which is supposedly to be less than 30%. However, based on the analysis, most of the surface showed the opposing result as can be seen in Figure 4(a), while diorite and syenite, which is intermediate or mesocratic rocks contained

30%–60% of dark minerals by referring to Figure 4(b) and (c). Gabbro, the melanocratic or basic igneous rocks contained more than 60% dark minerals. Finally, peridotite, a hypermelanic or ultrabasic igneous rock, shows that most of the sides of sample contained dark minerals [Figure 4(e)].

Despite showing consistency between increment in percentage of black pixels and colour of rock (as in Figure 1), not all types of rocks fit the definition provided.[1] For example, the analysis on biotite granite showing percentage of black pixels below 30%.

4. CONCLUSION

Based on the results, several conclusions and recommendations had been made:

1. There is a significant difference in the image analysis due to the blurring and unclear images captured from the small rock samples. This is not reflected on the whole rock mass. Therefore, it is recommended to use a high-definition camera with automatic zooming setting to avoid blurred images.
2. The binary approach has been successfully employed and the images were successfully converted to determine the percentage of black pixels. It is recommended to study and use other digital image processing methods such as the grayscale approach for determining dark minerals in igneous rocks. A study on the effect of different threshold values (other than default value 0.5) is also recommended, in order to see if all rocks can fit into the definition provided.[1]

5. ACKNOWLEDGEMENT

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