ROCK IMAGE RETRIEVAL AND CLASSIFICATION BASED ON GRANULARITY

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ABSTRACT

In this paper, we consider the use of texture granularity in the classification and retrieval of natural rock images. In rock science, the rock images are nowadays stored into large image databases. In the images, there often occur large grains which differ clearly from rock texture. The purpose of this work is to find grain rock images from the database. We present two approaches to this purpose: classification and retrieval approach. In both approaches, the grains of desired color and size are recognized from the database images using color analysis combined with morphological tools. The experimental results show that using our method, the images with grain can be distinguished from the other rock images.

1. INTRODUCTION

Recently the number of different image databases has increased remarkably. These databases contain nowadays e.g. photographs, medical images, or satellite images. Due to the strong growth on this field, image database retrieval [7] and classification have become popular research areas. Usually the classification and retrieval of the database images are based on their similarity. The similarity between the database images is usually defined based on visual features extracted from the images.

Classification of natural images is one research task on this area. The division of natural images like rock, stone, clouds, ice, or vegetation into classes based on their visual similarity is a common task in many machine vision and image analysis solutions. Classification of natural images is demanding, because in the nature the objects are seldom homogenous. On the contrary, the natural images may have strong non-homogeneities in their texture or color distribution. For example, when the images of rock surface are inspected, there are often strong differences in directionality [4], granularity, or color of the rock, even if the images represented the same rock type. These kinds of variations make it difficult to classify these images accurately.

Texture [5] is an important image descriptor in the content-based image classification and retrieval. Also in the analysis of natural images, texture plays a remarkable role. In the description of image texture, it is essential to consider human texture perception. Rao and Lohse [6] indicated that three most important perceptual dimensions in the natural texture discrimination are repetitiveness, directionality and granularity. The directionality of non-homogenous natural textures has been discussed in our earlier work [3], [4]. This study considers the texture granularity in the analysis of natural rock images.

In this paper, we present our approach to the granularity-based retrieval and classification of natural rock texture images. Our purpose is to find images with grains (phenocrysts) of a particular size and color from a rock image database. In the rock textures, granularity is often non-homogenous, because the size and shape of the grains may have strong variations. In the recognition of the texture grains, we use color analysis tools combined with morphological operators. This way the rock samples containing grains can be recognized from the database.

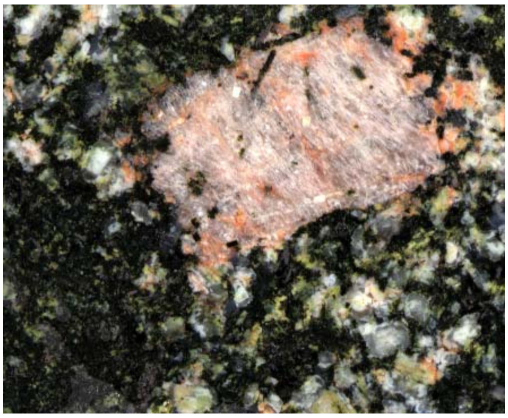

Figure 1. An example of rock texture image that contains a large grain.

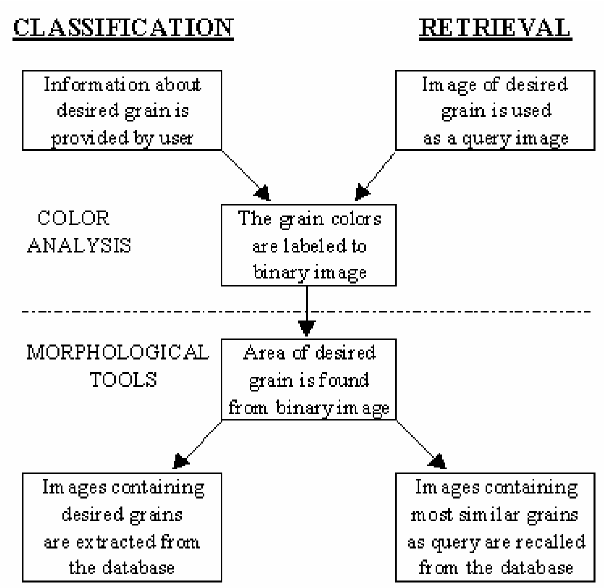

Figure 2. An outline of the classification and retrieval system.

2. ROCK IMAGE DATABASE

In the field of rock science, the development of digital imaging has made it possible to store and manage the images of the rock material in digital form. One typical application area of the rock imaging is bedrock investigation. In this kind of analysis, rock properties are analyzed by inspecting the images which are collected from the bedrock. These images can be stored into image databases, which may contain thousands of rock images. Therefore, analysis methods are needed to organize these databases.

In this paper, we consider the analysis of a database that consists of non-homogenous rock images. A part of the database images contain a clearly visible, large grain. The grain is defined as a relatively large connected area of certain color, which differs clearly from the background texture. The purpose of this study is to detect the database images with these kinds of grains. Figure 1 shows an example of rock texture image that contains a pink grain. The grain is a smooth region which is surrounded by rock texture that has totally different color.

3. METHODOLOGY

In our algorithm, there are two possible approaches: retrieval and classification. The outline of the system is presented in figure 2. In the case of classification, the information about grain color and size are provided by the user. The algorithm classifies the images of a desired grain into a particular category. In retrieval, an image of a desired grain type is used as a query image. The algorithm recalls then the images containing the most similar grains from the database.

In this paper, we use color and texture information of the rock images to find grains from the rock texture. For this purpose, we find regions of desired color distribution. These regions are then analyzed using morphological image analysis. Hence the grain recognition procedure presented in figure 2 is twofold: the color analysis is followed by morphological operations.

2.1. Color analysis

In the color-based grain detection, we use the histogram-based color matching algorithm. The idea of this type of approach was presented by Swain and Ballard [8]. In their Backprojection algorithm, the aim was to find region of desired color distribution from the image. Ennesser et al. [1] made further development on this field. In their approach, the local histogram of an object was matched with the image to find the object from the image.

In the case of retrieval, we find the regions containing the same local color histogram as the query grain. This is made by finding the pixels of the same colors as in the histogram of the query

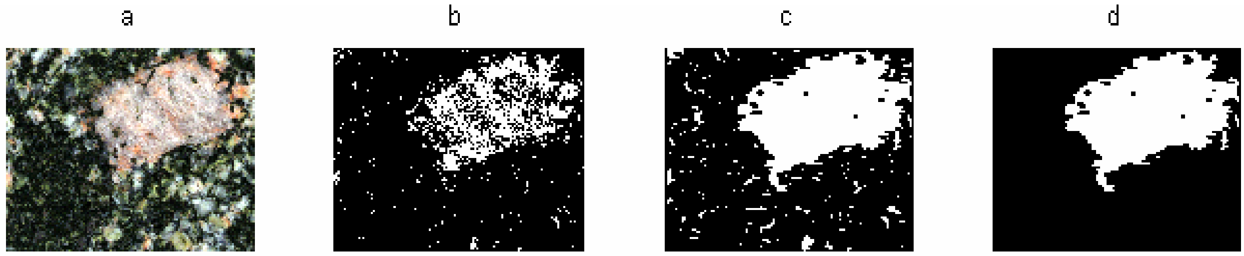

Figure 3. The procedure for grain detection. a) An example image, b) the regions of interest defined by color analysis as binary image, c) binary image after closing, d) the largest connected region of the image.

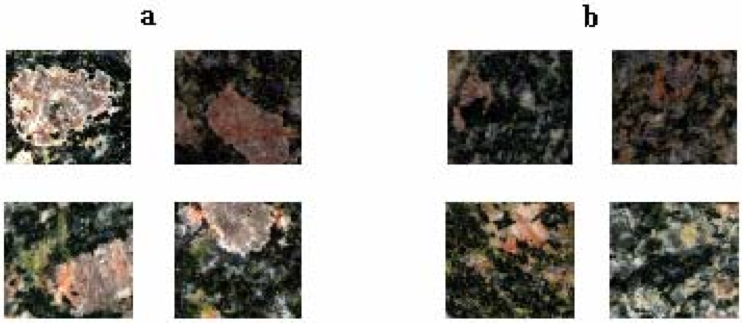

Figure 4. Example images of the test set that consists of grained images (a) and the images without grain (b).

grain. This results a binary image, in which the pixels of desired colors are marked with one and the rest of the pixels are zeros. Hence the nonzero regions represent the areas of a possible grain.

In the classification approach, the user defines the color distribution of desired grains. Then the algorithm simply finds the colors provided by user. This is made by thresholding the database images based on the color set [2]. This way, similar binary representation as in the case of retrieval approach can be achieved. In figure 3b is presented the binary image obtained from an example image of figure 3a.

2.2. Morphological operations

In the color analysis, the algorithm labels the regions of possible grain in the database images. In the binary image, the grains represented by connected regions of a certain color distribution can be detected. However, all of these regions do not necessarily represent a grain, because grain size is not considered in the color analysis. Also in many cases single pixels of desired color form weakly connected areas that are not grains. Therefore, we apply morphological tools [2] to the binary images produced in color analysis.

In the example of figure 3c, the binary image of figure 3b is cleaned using morphological closing operation. Closing of binary image $\mathbf{I}_B$ using a structuring element $\mathbf{S}$ is defined as dilation followed by erosion [2]:

$$\mathrm{close}(\mathbf{I}_B, \mathbf{S}) = \mathrm{er}\left(\mathrm{dil}(\mathbf{I}_B, -\mathbf{S}), -\mathbf{S}\right) \qquad (1)$$

This way connected regions can be recognized from the binary image.

2.3. Retrieval and classification

After the use of the morphological operations, the resulting binary regions are labeled and sorted based on their area. Then it is easy to find regions of desired grain size. In the case of retrieval, the images containing grain regions of about the same size as the query grain are recalled. In classification, all the images that contain a grain with desired properties are extracted from the database.

3. EXPERIMENTS

In this part of the paper, we make experiments using a database of rock images. The image database consists of 336 samples (200x220 pixels) collected from large rock images. The database is divided into two classes: grained images and the images without grain. In the grained images, there is a clearly visible reddish grain surrounded by rock texture. The number of the grained images in the database is 76. In the class of images without grain, there are the rest of the rock samples, 260 images. However, the texture of these images is similar to the background texture of grained images. Example images of these classes are presented in figure 4. The goal of the experiments was to make a classification between these image classes.

In the classification experiments, the color distribution of grains was defined in HSI-color space. The grain color was described using hue (H) component of the image. The color and size of the desired grain type in each class was defined based on manual inspection of the samples. The grain size was limited by giving a minimum value to the area, which is considered as a grain. This way the images containing smaller areas were not considered as a grain.

The classification experiments were carried out by finding the grained images from the database. The resulting set of grained images contained 70 images with clearly visible grain. Because the total number of grained images in the database was 76, the classification system was able to find 92% of the grained images.

4. DISCUSSION

In this paper, we have presented a method for detecting rock texture images with a grain from the image database. The recognition of the grains is an essential task in the geological image analysis. Therefore, automatic methods for grain recognition are needed.

Rock texture images, like all natural textures, are often non-homogenous. Also in the case of grains, there are strong differences in their size, shape and color. This makes the grain recognition a demanding task. The grain and texture surrounding it have sometimes very similar color distribution, which makes the grain detection more difficult. However, using the color information of the desired grain, the grain region can be recognized.

Our method uses color analysis that is combined with morphological tools. Hence the areas of desired colors are inspected using morphology. This way, the connected regions of desired color can be recognized as grains. The experimental results show that the method can find the grained images from the database accurately. Therefore, this method can be applied to the classification and retrieval of grained rock images.

5. ACKNOWLEDGMENT

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