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Research paper

Unsupervised feature learning for autonomous rock image classification

Lei Shu[a,b,*], Kenneth McIsaac[a,b], Gordon R. Osinski[b,c], Raymond Francis[d]

[a] Department of Electrical and Computer Engineering, University of Western Ontario, 1151 Richmond St, London, ON, Canada N6A 5B7
[b] Centre for Planetary Science and Exploration, University of Western Ontario, 1151 Richmond St, London, ON, Canada N6A 5B7
[c] Department of Earth Science, Physics and Astronomy, University of Western Ontario, 1151 Richmond St, London, ON, Canada N6A 5B7
[d] Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr, Pasadena, CA 91109 United States

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ABSTRACT

Autonomous rock image classification can enhance the capability of robots for geological detection and enlarge the scientific returns, both in investigation on Earth and planetary surface exploration on Mars. Since rock textural images are usually inhomogeneous and manually hand-crafting features is not always reliable, we propose an unsupervised feature learning method to autonomously learn the feature representation for rock images. In our tests, rock image classification using the learned features shows that the learned features can outperform manually selected features. Self-taught learning is also proposed to learn the feature representation from a large database of unlabelled rock images of mixed class. The learned features can then be used repeatedly for classification of any subclass. This takes advantage of the large dataset of unlabelled rock images and learns a general feature representation for many kinds of rocks. We show experimental results supporting the feasibility of self-taught learning on rock images.

1. Introduction

1.1. Background and motivation

Autonomous geological detection is becoming an increasingly important technique for robotic platforms exploring remote environments such as Mars (e.g. Francis et al. (2014a), (2014b)). It can maximize the scientific return and reduce the need for human involvement. In the case of Mars specifically, the bandwidth limit and large time delay (3–22 min one-way travel time) of data transmission makes autonomous techniques even more critical and valuable. The past two decades have seen tremendous achievements in Mars exploration. Among them are Mars Exploration Rovers (MER) and Mars Science Laboratory (MSL) missions. Both missions sent rovers to the surface of Mars and explored their respective regions of interest with various scientific instruments. Two autonomous onboard systems have been developed for these rovers: the Onboard Autonomous Science Investigation System(OASIS) (Castano et al., 2004, 2007, 2008), and the Autonomous Exploration for Gathering Increased Science(AEGIS) system (Estlin et al., 2009, 2012). Both systems are actively used and have enabled the rovers to autonomously identify and react to serendipitous science opportunities by analyzing imagery onboard with computer vision techniques. Tasks included locating rocks in the images, analyzing rock properties, and identifying rocks that merit further investigation through autonomous selection and sequencing of targeted observations. However, the rovers still heavily rely on explicit instructions given by scientists on Earth, which requires extensive communication and frequent command cycles. As such, there is still a long way to go before rovers will possess sufficient “intelligence” to reason about science goals, make informed decisions, and respond to discoveries autonomously (Francis et al., 2014b).

An alternative approach to AEGIS and OASIS is increasingly being used in geosciences in the form of computer vision. For example, Chanou et al. (2014) and Pittarello and Koeberl (2013) developed and applied quantitative image analysis methods to analyze the images of individual rock samples. In these approaches, components or particles of a rock image are first segmented, which then allows the measurement and quantification of various properties, such as shape complexity, preferred orientation, size-frequency, and so on. A different advanced technique that we focus on here is rock image classification (Shang and Barnes, 2012). Instead of the exact quantitative measurement of particles in rock images, the approach of rock image classification is to identify the specific type of rock(s) based on visual appearance. The identification of rock type is important as this provides information as to the environment in which the rock was created and its subsequently geological history (Gor et al., 2001). For example, the size of crystals in igneous rocks can be used to estimate cooling rates and provides constraints on the depth of formation; the

* Corresponding author at: Department of Electrical and Computer Engineering, University of Western Ontario, 1151 Richmond St, London, ON, Canada N6A 5B7.
E-mail address: lshu2@uwo.ca (L. Shu).

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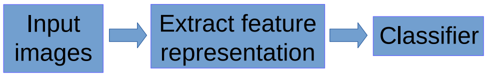

Fig. 1. The typical framework of image classification.

grain size and shape of sedimentary rocks provides information as to the mode of deposition; and the properties of rocks formed by meteorite impact craters reflects the pressure and temperature of formation and of the environment prior to impact. As such, autonomous rock classification has the potential to provide valuable information about the origin and evolution of rocky planetary bodies throughout the Solar System.

1.2. Related work

A typical framework of image classification (see Fig. 1) includes extracting feature representation for input images and feeding the feature representation into a classifier. In general, the performance of image classifiers is heavily dependent on the selection of a feature representation. Unfortunately, rock textures are seldom homogeneous. As a result, the design of a feature representation is difficult, which makes rock image classification extremely challenging. There have been a few attempts at developing feature representation for rock image classification to date. All these previous works use either hand-engineered features manually selected for the specific application, or automatically selected features chosen using time-consuming methods.

Prior works mostly involve manually selected features. In order to reduce the time-consuming process of manual identification of rock samples, Ślipek and Młynarczuk (2013) and Młynarczuk and Górszczyk (2013) conducted autonomous classification of microscopic images of rocks by four pattern recognition methods - nearest neighbour, k-nearest neighbours (k-NN), nearest mode, and optimal spherical neighbourhoods. Sharif et al. (2015) built a small library of grayscale images from a total of 30 hand samples, and used Bayesian analysis to classify them with selected Haralick textural features (Haralick et al., 1973). In order to distinguish adjacent outcrops, Francis et al. (2014a) started with some fundamental visual "channels" such as colour and difference between colour channels, then utilized multi-class linear discriminant analysis (MDA) to identify the principal visual components. Harinie et al. (2012) utilized Tamura features (Tamura et al., 1978) to classify hand samples of rocks into the three major categories, namely, igneous, sedimentary and metamorphic. Dunlop (2006) studied features such as shape, albedo, colour and textures, then conducted rock classification with different feature combinations. Singh et al. (2004) compared 7 well-established image texture analysis algorithms for rocks classification and the results suggested that Law's masks (Laws, 1980) and co-occurrence matrices (Haralick et al., 1973) were best. Lepistö et al. (2003) classified rock images by methods based on textural and spectral features. The spectral features are some colour parameters and the textural features are calculated from the co-occurrence matrix. In order to improve the classification accuracy, Lepistö et al. (2005) combined colour information in Gabor space (Tou et al., 2007) to the texture description. Given that various visual descriptors extracted from images are often high dimensional and non-homogenous, Lepistö et al. (2006b) conducted rock images classification based on k-nearest neighbour voting, which combined k-NN base classifiers for different descriptors by voting. A similar idea of combining base classifiers came to Lepistö et al. (2006a). Each feature descriptor had a corresponding separate base classifier, and better classification accuracy can be achieved by combining opinions provided by each base classifier.

Other works have concentrated on feature selection. Chatterjee (2013) used the genetic algorithm to select features, and then classified limestone with multi-class SVM (Support Vector Machine). Shang and Barnes (2012) utilized a reliability-based method and mutual information to select features, then classified rocks images in a more general dataset. Both works showed that their own feature selection methods worked well in their dataset, but feature selection itself is time-consuming. When the dataset becomes complicated, one might have to think of what kind of feature pool to select from, or even devising a brand new feature representation.

All the previous representations used for rock images consist either of an entirely manually crafted feature set or a set of features automatically selected from a set of manually crafted features. These manual features are not good enough to represent inhomogeneous rock images and are time-consuming to get. Our proposed methods address this deficiency by automatically learning the feature representations. Our experimental results demonstrate that the learned feature representations have the potential to be more flexible and powerful.

1.3. Introduction to this study

We have approached the problem of feature selection for geological classification in two ways in this paper. First, we propose an unsupervised feature learning technique (Coates et al., 2011) to extract features for rock images. The approach is to autonomously learn the feature representation from a large amount of data rather than manually choosing the features. This has the benefit of making the feature representation much more flexible when using different datasets. The feature learning method we utilized is based on K-means (Coates and Ng, 2012), which is fast and easily implemented. We applied this method to the classification of rock images with SVM (Support Vector Machine). (Both K-means and SVM are described below).

The second autonomous feature selection method we propose in this paper is called self-taught learning (Raina et al., 2007; Wang et al., 2013). The concept behind self-taught learning is to learn a feature representation from unlabelled images of *mixed-class* and then train a classifier on a *subset of the data* that has been labelled to identify certain subclasses represented within the original data set. For image classification, having enough labelled images is important. Basically, the more images you have, the better learning you get. However, it is usually difficult and expensive to label images. Though researchers have resorted to tools such as AMT (Amazon Mechanical Turk) to have a large number of people help with labelling, there are still financial costs and concerns about the quality of labelling. Thus the ability to use *unlabelled images* would greatly enhance an autonomous feature identification technique. In addition, it is highly unlikely that a particular dataset will only contain the classes of the images we are interested in. It is much more likely that a dataset will comprise a mix of all kinds of possible rock classes. As such, we utilized self-taught learning to directly learn feature representation from unlabelled rock images of mixed-class and then applied the feature representation to labelled rock images which we are interested in for classification. In such an approach, the unlabelled images do not have to follow the same distribution as the labelled images, and the labelled images for classification can belong to merely subclasses of the unlabelled images (Raina, 2009). This attribute is particularly important for applications such as planetary exploration where the potential rock types will be uncertain.

Below, we first present the rock image dataset. Next we provide background on the set of manually selected features, the K-means feature learning approach and the self-taught learning approach. Finally, we show the effects of parameter selection for the feature learning methods as well as the results of classification with both the manual features and both types of learned features.

2. Rock image dataset

We photographed 9 different types of rock hand samples to generate a rock image dataset. The samples are provided by Department of Earth Science in Western University. These rocks are