Automatic detection of Martian dark slope streaks by machine learning using HiRISE images

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ABSTRACT

Dark slope streaks (DSSs) on the Martian surface are one of the active geologic features that can be observed on Mars nowadays. The detection of DSS is a prerequisite for studying its appearance, morphology, and distribution to reveal its underlying geological mechanisms. In addition, increasingly massive amounts of Mars high resolution data are now available. Hence, an automatic detection method for locating DSSs is highly desirable. In this research, we present an automatic DSS detection method by combining interest region extraction and machine learning techniques. The interest region extraction combines gradient and regional grayscale information. Moreover, a novel recognition strategy is proposed that takes the normalized minimum bounding rectangles (MBRs) of the extracted regions to calculate the Local Binary Pattern (LBP) feature and train a DSS classifier using the Adaboost machine learning algorithm. Comparative experiments using five different feature descriptors and three different machine learning algorithms show the superiority of the proposed method. Experimental results utilizing 888 extracted region samples from 28 HiRISE images show that the overall detection accuracy of our proposed method is 92.4%, with a true positive rate of 79.1% and false positive rate of 3.7%, which in particular indicates great performance of the method at eliminating non-DSS regions.

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1. Introduction

Dark slope streaks (DSSs) are seen on the surface of Mars as dark, narrow, fan shaped features (e.g., Fig. 1) that appear on slopes covered by dust at low latitudes (Schörghofer, 2014). Observations from multiple coverage images show that fresh DSSs are darker than their surrounding area, then gradually fade away over time, finally merging with the background and disappearing (Carr, 2007; Gremminger, 2005–2006). The interest in investigating DSS arises because it is one of the active geologic features that can currently be observed on Mars. Study of its morphologies, distributions and changes, (Sullivan et al., 2001; Schorghofer and King, 2011) are important for revealing and understanding its formation mechanisms (Burleigh et al., 2012; King 2005–2006; Aharonson et al., 2003), inner geological structure (Gerstell et al., 2004), relations with atmospheric action (Cantor, 2007; Chuang et al., 2010; Baratoux et al., 2006), surface composition (Ojha et al., 2015), and other fields (Schorghofer et al., 2002). Before these studies can be carried out, detection of DSSs is the first basic step.

According to Baratoux’s statistics (Baratoux et al., 2006), the widths of DSSs mostly range from 25 to 125 m, and many streaks can only be clearly observable and confirmed on high resolution images. In the past, this work was mainly done manually (Schorghofer et al., 2002; Bergonio et al., 2013; Chuang et al., 2007). Currently, high resolution data from several missions are still being released each year. Nevertheless, the coverage of Mars at a resolution finer than 2 m/pixel is still low. In the near future, there will be more missions carrying high resolution sensors. With the increasingly massive amounts of Mars high resolution data available now and in the future, an automatic detection method is highly desirable.

Before the development of automatic approaches, manual extraction method was used: Schorghofer et al. (2007) studied slope steak activity in five areas by manually comparing Viking observations in 1977–1980 and Mars Orbiter Camera (MOC) observations 1998–2005; Aharonson et al. (2003) performed a global analysis of the slope streaks by manually examining 29,326 MOC narrow angle images and found slope streaks in 1386 images; Baratoux et al. (2006) manually identified and measured the
lengths, widths, and directions of DSSs in two regions and analyzed these properties with respect to factors such as terrain, wind direction, and surface roughness.

As manual work is time consuming, some automatic DSS extraction methods have been developed recently. Di et al. (2014a) used a context window that calculates the grayscale gradients for each pixel in the image, then set a threshold to choose the pixels that have high contrast against the background to form the DSS regions. However, the work did not include a recognition stage, so the extracted regions need the further confirmation of an expert. Wagstaff et al. (2012) computed the entropy in a local window for every pixel and picked the pixels with entropy higher than a certain threshold to form a region. They then used its shape properties and simple grayscale information to train a classifier. For DSSs that are located in more complicated backgrounds, these region descriptions are not sufficient to describe the target. Given the few previous works on DSS detection, machine learning is a promising approach that would save manual recognition time.

For other geology features, especially for craters, numerous machine learning detection methods have been proposed (Burl et al., 2001; Vinogradova et al., 2002; Martins et al., 2009; Ding et al., 2013; Cohen and Ding, 2014; Di et al., 2014b). Given crater characteristics, a window-based machine learning method is always employed. The typical way to implement a window-based machine learning approach is to use square windows that each includes a crater as positive samples, and windows without craters as negative samples. Then a feature description method is used to extract the characteristics of both positive and negative samples. With the extracted feature descriptions and the labels of the samples, a machine learning model is applied to train a classifier. When testing a new image, multiple scale sliding square windows are used to traverse the entire image, and the classifier is used to judge whether the current square window contains a crater. The final results are obtained by eliminating the reduplicative squares. If the contour of the crater is needed, edge extraction and ellipse fitting should be done in the identified square (Kim and Muller, 2005). Because a DSS is slender and often appears very close to adjacent ones, the window-based method is not appropriate in this case. Using this window-based method, in some cases, a DSS may only cover a small part of the entire window, meanwhile the window may include portions of adjacent DSSs and other surface features (see Fig. 1). In this way, the features for describing a window containing a DSS as positive samples are indistinguishable enough such that an effective classification is not achievable (Cheng et al., 2014). Another mode of pattern recognition is to use object-based methods (Chen et al., 2014; Blaschke, 2010; Mallinis et al., 2008), i.e., first forming regions obtained by a certain segmentation algorithm (such as those described in Di et al. (2014a) and Wagstaff et al. (2012) and other methods: clustering (Maulik and Saha, 2010), region growing (Yu and Clausi, 2008), etc.), and then training the classifier using the features extracted from the regions. The segmentation step must be applied to the new images for identification before applying the classifier. However, object-based recognition methods only focus on grayscale or shape features within the contour, ignoring the adjacent grayscale information, which is the prominent characteristic of a DSS. A DSS lacks texture information on its surface, hence the grayscale difference between the inside and outside of the DSS is its distinguishable characteristic. If this information can be taken into account, it may improve the recognition accuracy.

In this study, we present an automatic DSS detection approach that combines region extraction and machine learning techniques. The data used in this study is briefly introduced in Section 2. In Section 3, we first present the interest region extraction process that combines gradient and regional grayscale information. A novel recognition strategy that considers the texture inside the extracted regions as well as the imaging characteristics of its surrounding area is then proposed. Section 4 presents the experiment results based on our proposed method. Finally, the conclusion is given in Section 5.
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