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ScienceDirect

Advances in Space Research 56 (2015) 982–991

ADVANCES IN SPACE RESEARCH
(a COSPAR publication)

www.elsevier.com/locate/asr

A novel sparse boosting method for crater detection in the high resolution planetary image

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Received 19 January 2015; received in revised form 31 March 2015; accepted 6 May 2015
Available online 16 May 2015

Abstract

Impact craters distributed on planetary surface become one of the main barriers during the soft landing of planetary probes. In order to accelerate the crater detection, in this paper, we present a new sparse boosting (SparseBoost) method for automatic detection of sub-kilometer craters. The SparseBoost method integrates an improved sparse kernel density estimator (RSDE-WL1) into the Boost algorithm and the RSDE-WL1 estimator is achieved by introducing weighted l_1 penalty term into the reduced set density estimator. An iterative algorithm is proposed to implement the RSDE-WL1. The SparseBoost algorithm has the advantage of fewer selected features and simpler representation of the weak classifiers compared with the Boost algorithm. Our SparseBoost based crater detection method is evaluated on a large and high resolution image of Martian surface. Experimental results demonstrate that the proposed method can achieve less computational complexity in comparison with other crater detection methods in terms of selected features.

Keywords: Crater detection; Reduce set density estimator; Boosting; Feature selection; Classification

1. Introduction

Impact craters, formed by collisions of meteoroids with planetary surface, are among the most studied geomorphic features in the solar system. Containing information about the past and present geological processes, craters provide the effective tool for measuring relative ages of observed geologic formations (Tanaka, 1986). Because of such importance, various researchers are collecting datasets of craters and attempting to build the information database of craters (Rodionova et al., 2000; Barlow, 2003; Robbins and Hynek, 2012). In addition, during the soft landing of planetary probes the abundant craters distributed on planetary surface serve as the main obstacles, which requires some efficient approaches for their detection.

Manual detection pays attention mainly to large craters of planetary images. In the work by Barlow (1988), 42,283 Martian craters with diameters larger than 5 km are studied and 8497 lunar craters with diameters larger than a few kilometers are identified in the work by Andersson and Whitaker (1982). Robbins and Hynek (2012) supply the largest Martian crater database that contains Martian craters with diameters ranging from 1 km to 512 km. It is well-known that on planetary surface large craters are rare while small craters are abundant. The literature on crater detections algorithms (CDAs) is extensive. Salamuniccar and Loncaric (2010) and Salamuniccar et al. (2011) displays 77 past publications on various CDA approaches, however, no algorithms can be capable of becoming a standard tool for practitioners of planetary science. Crater counts continue to be done via manually visual inspection

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http://dx.doi.org/10.1016/j.asr.2015.05.014
0273-1177/

of images even as data sets of high resolution images keep on increasing. Therefore, it is necessary to survey such small craters by crater auto-detection techniques.

Several attempts to create reliable methods for autonomous crater detection have been developed. In general, the methods of autonomous crater detection can be divided into three categories: unsupervised, supervised and combinative methods.

Unsupervised methods identify crater rims in an image as circular or elliptical features and apply the related theory of image process and object detection to detect craters, including approaches of Hough transform (HT) and its improved algorithms (Bue and Stepinski, 2007; Giulia et al., 2012), genetic algorithm (GA) (Honda et al., 2002), radial consistency (Earl et al., 2005) and template matching (Banderia et al., 2007; Ding et al., 2009). Unsupervised methods have the advantage of being fully autonomous without a large number of labeled examples to learn an accurate classifier. These methods work well in the limited context of an autonomous spacecraft navigation system, but are not robust when applied to the images containing complex terrain.

The supervised methods take advantage of domain knowledge in the form of labeled training sets and use machine learning conception to construct classifiers, such as neural network (Kim et al., 2005), support vector machine (SVM) (Wetzler et al., 2005) and Adaboost approach (Martins et al., 2009). These methods concentrate on the classification component of crater detection, but do not take the identification of crater candidates into account. Urbach and Stepinski (2009) came up with the idea of finding crater candidates. Crater candidates are the regions that may contain craters in an image. They can be recognized as a pair of crescent-like highlights and shadows. In the work by Urbach and Stepinski (2009), the shapes of the highlight and shadow regions in crater candidates are expressed by a small set of features. However, it is not a proper choice for crater detection when other non-crater landforms are in similar shapes. Ding et al. (2011) proposed an integrated framework on crater detection with boosting and transfer learning. In this framework, they used the idea of crater candidates in Urbach and Stepinski (2009), and extracted image texture features from crater candidates. Texture features enrich the information for crater detection. Then, several supervised learning algorithms are used to select a small set of features and identify crater candidates into craters and non-craters.

The combinative methods employ multiple approaches including unsupervised and supervised methods to improve the rate of cater detection (Sawabe et al., 2006; Ding et al., 2013). They often offer image patches as the input of supervised methods. On the combination of template matching and neural network in the process of detection, Kim et al. (2005) make use of neural network to train various templates to increase the recognition rate.

In a word, the methods above can detect the craters in large size or sub-kilometer size in some effective ways. But when the number of craters needed to be identified is abundant, traditional crater detection methods have the disadvantages of high computational complexity in time and space. Therefore it is necessary and significant to study the fast and accurate crater detection methods.

In this paper, we develop the supervised method to detect the abundant craters in sub-kilometer size. Based on the framework for crater detection presented by Ding et al. (2011), a new sparse boosting (SparseBoost) method is presented. The SparseBoost method integrates an improved sparse kernel density estimator (RSDE-WL1) into the Boost algorithm. Reduced set density estimator (RSDE), employing a small percentage of available data samples, is an effective and important nonparametric technique for probability density function estimation (Girolami and He, 2003). Dealing with its high complexity in time and space, we introduce the weighted l_1 norm of the estimated coefficients as penalty term into the RSDE. The proposed iterative algorithm is used to solve the corresponding convex optimization problem efficiently and the RSDE-WL1 estimator is obtained. The advantage of the RSDE-WL1 is that it can achieve superior performance in sparsity and complexity in density estimation. The Boost algorithm is a boosting algorithm for feature selection and classification in crater detection. To deal with the large size of the training set and reduce the computational complexity, we use the proposed RSDE-WL1 to construct the weak classifiers and combine them through a weighted boosting approach to build the strong ensemble classifier. The proposed SparseBoost algorithm is evaluated on a large and high-resolution image of Martian surface, featuring high density of small sub-kilometer craters and spatial variability of crater morphology. The experimental results demonstrate that our method is superior to other related methods in prediction accuracy and computational complexity.

The rest of the paper is organized as follows. Section 2 presents the main framework of the proposed crater detection method. Section 2.1 and 2.2 explain how to find crater candidates and extract image texture features from those crater candidates. Section 2.3 introduces our sparse boosting algorithm used for feature selection and classification. Section 3 gives the experimental study on identifying craters in a large, high-resolution planetary image. The last section summarizes our work and discusses its actual application.

2. Crater detection based on SparseBoost algorithm

In this section, an approach integrating the proposed RSDE-WL1 into the Boost algorithm is presented for rapid crater detection. Fig. 1 shows the main framework of our method for crater auto-detection. It contains four steps: (1) Image preprocessing and finding crater candidates. (2) Extracting texture features from crater candidates. (3) Combining the proposed RSDE-WL1 with the Boost algorithm and building the sparse boosting classifier (SparseBoost classifier). (4) Training the SparseBoost