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Crater monitoring through social media observations

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Abstract

Lunar craters have attracted the attention of not only scientists but also citizens. Modern high-resolution cameras with zoom capabilities allow citizens to capture and share pictures of the Moon in Social Media platforms, such as Twitter. We have collected 69 pictures of the Moon, from 01-01-2017 to 17-04-2017, that have been uploaded on Twitter and have been associated with the keyword *#crater*. The lunar pictures are indexed using SIFT descriptors and are then clustered using density-based approaches to group them into the automatically detected levels of zoom.

1. Introduction

The automatic detection and classification of lunar craters have been one of the most important challenges among lunar experts. Several approaches have been proposed [7] to detect or count craters, in order to assist and accelerate the classification of space images. Crater shapes are changing in time and their transition to a more complex morphology has been investigated [5]. Other approaches involve the extraction of visual descriptors that are based on the Hough transform for the detection and counting of craters [3]. Contrary to the use of lunar catalogues of optical images [6], we propose in this work the monitoring of crater activity through social media observations.

2. Methodology and Results

We crawled from the Twitter API[1] 69 pictures of the Moon, from 01-01-2017 to 17-04-2017, in response to the keyword *#crater*. In Table 1 we present the number of pictures per month and the daily coverage:

$$\text{Daily coverage} = \frac{\text{number of pictures per month}}{\text{number of days per month}} \tag{1}$$

[1]https://dev.twitter.com

From each crawled Twitter image, we extract salient points using the Lip-vireo[2] tool, in order to index all images using SIFT descriptors [4]. The Bag-of-Visual-Words representation is followed [2] using term frequency - inverse document frequency (tf-idf) scores, using a visual vocabulary of 100 visual words, obtained by k-means clustering with 30 iterations to ensure convergence in the visual vocabulary creation.

Table 1: Uploaded pictures per month.

Month	Pictures	Daily Coverage
January	23	74.19%
February	19	67.86%
March	16	51.61%
April (1st-17th)	11	64.70%

After the indexing of each image, an OPTICS reachability plot [1] is employed to visualize the cluster structure, i.e. the number of clusters and the optimal density level. The OPTICS reachability plot indicates that the dataset has two density-connected groups of pictures (clusters), which are extracted at the density level $\epsilon = 0.05$, while a lower bound for the number of pictures per cluster is $minPts = 5$. The adoption of a density-based clustering approach allows the presence of noise in the dataset and does not require a priori knowledge of the number of clusters. In Figure 1 we present a sample of the two detected groups of lunar images and one additional group of images (noise).

3. Summary and Conclusions

We have collected more than one image per two days, on average, in response to the keyword *#crater*. Each one of the collected images has been clustered into two main groups of images and an additional cluster is provided (noise) with pictures that have not been assigned to any cluster. The proposed lunar image

[2]http://pami.xmu.edu.cn/ wlzhao/lip-vireo.htm

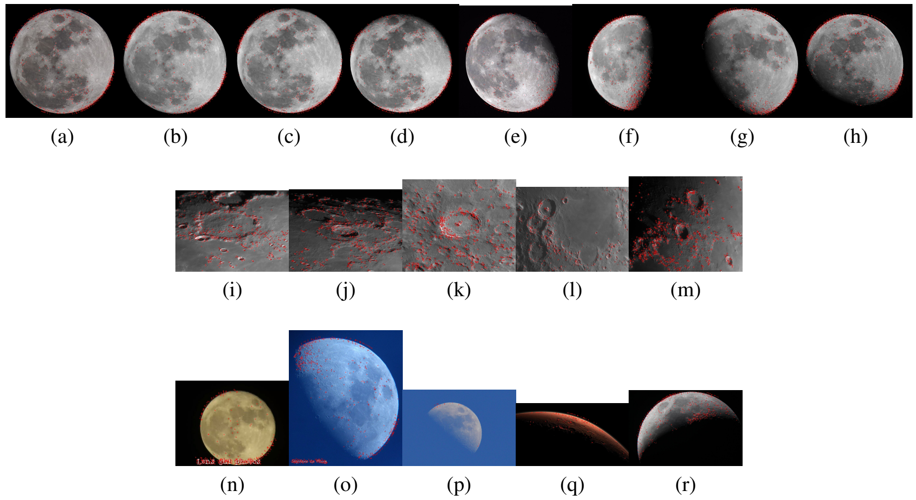

Figure 1: Sample of the pictures per group. The salient points that have been detected are shown on each image. The first group of pictures (a)-(h) shows a complete facet of the Moon, while the second group (i)-(m) zooms into craters. The last group (n)-(r) belongs to the set of unassigned pictures to any of the first two groups (noise).

clustering process provides two classes of lunar pictures, at different zoom levels; the first showing a clear view of craters grouped into one cluster and the second demonstrating a complete view of the Moon at various phases that are correlated with the crawling date. The clustering stage is unsupervised, so new topics can be detected on-the-fly. We have provided additional sources of planetary images using crowd-sourcing information, which is associated with meta-data such as time, text, location, links to other users and other related posts. This content has crater information that can be fused with other planetary data to enhance crater monitoring. The classification of each new Twitter picture is marked as relevant manually, but we plan to train a binary classifier for that purpose.

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