# Textural Analysis of the Lunar Surface using a Shaded Digital Elevation Model.

Martin J. Vickers[1] and Anthony C. Cook[1], [1]Institute of Mathematics and Physics, Aberystwyth University, Aberystwyth, Wales, UK (mjv08@aber.ac.uk)

High resolution satellite imagery is more available than ever. The first release of Lunar Reconnaissance Orbiter Camera (LROC) data on NASA's Planetary Data System totaled ∼50TB in the first six months alone [1]. Machine vision techniques would provide an advantage when exploring these vast amounts of data. However varying view and illumination angles (phase angles) make it difficult to accurately classify textures when viewing remotely sensed imagery taken at different times.

In an effort to solve this type of phase angle problem when dealing with textures, Varma and Zisserman [2] demonstrated the Leung and Malik [3] Texton technique for multiple images of the same texture with varying phase angles, such as those found in the CUReT database [4].

This paper presents the application of this automated texture classification technique to a lunar Digital Elevation Model (DEM). The aim is to assist researchers to search through this vast amount of data for morphological features of interest as well as confirming past classifications.

**Texton analysis**

The Texon techniques described in [2] and [5] consist of three parts; preprocessing, training and classification. The CUReT database is used for analysis and contains a population of 61 samples containing 92 200x200 pixel images each. Preprocessing splits the population of images into two even disjointed subsets for training and classification respectively. All images are converted to greyscale and intensity normalised with zero mean and unit standard deviation.

The training part takes several images from each sample and extracts filtered [2] or Digital Number (DN) [5] patches depending upon the technique one is applying. Patches are row ordered and aggregated for each sample to be clustered using the K-Means method [6]. These clusters are known as Textons and form a 'model' that comparisons can be made with. In this example 13 images from each sample are selected at random and aggregated to produce 10 clusters per sample, therefore a 'model' of 610 Textons. Each image from each sample in the training set is compared to the 'model' creating a 'dictionary'. This is achieved by extracting the patches as before and finding the closest Texton within the model, thus creating a histogram. This produces a series of histograms to represent each sample.

Classification is performed by randomly selecting an image from the classification set and repeating the process of creating a histogram. This histogram is compared to each histogram in the 'dictionary' using the $\chi^2$ test to find the closest match.

**Texton Performance**

The [2] and [5] techniques are both implemented as described and results are displayed in Table 1. Once trained and a 'model' is created, classification is performed 50,000 times selecting random images from the classification set. The whole process is completed 3 times with identical criteria to obtain an average.

One point to note is that it is not clear in [2] and [5] how the two disjointed subsets of the CUReT population are selected. Since the images in each sample are in an order in relation to the phase angle, three methods have been implemented to explore the effects;

- HALF: The first half training and the second half classification
- RANDOM: A random selection of 46 none repeating images for training, the rest for classification
- EVEN: Every 'even' image selected for training, the rest for classification

| | Average Classification % | | |
|---|---|---|---|
| Patch Type | Half | Random | Even |
| 3x3 | 76.73 | 88.92 | 90.95 |
| 5x5 | 80.04 | 91.85 | 93.50 |
| 7x7 | 80.68 | 92.50 | 93.63 |
| 9x9 | 81.62 | 92.04 | 93.28 |
| LM49 | - | 89.52 | - |

Table 1: CUReT Results: Table showing the % of correct classifications of novel images. Note: LM49 filter technique [2] performed using randomly method only

As expected the 'EVEN' method of subset selection provides the largest classification results compared to 'RANDOM' and 'HALF'. This is due to the 'dictionary' comprising of an even spread of images across all phase angles. Also as observed in [5] a patch size of 7x7 outperforms the others.

### Textures using a DEM alone

The Texton method described in this paper, using a similar setup, was applied to images of craters created using the Lunar Terminator Visualization Tool (LTVT) [7]. The LTVT allows phase angles to be set by the user. The LOLA64 DEM [8] was used with the LTVT and no colour or shading other than the ray tracing shadow effects were applied. 30 large craters were selected and 20 images, viewed from directly above, were created using sub solar point 0° and 180° local azimuth, each with local elevation angles of 0-45° in 5° intervals in relation to the center of the crater. Each image contains the crater and is scaled to 200 x 200 pixel, normalised and as before two evenly selected disjointed subsets are selected using the 'EVEN' method as displayed in Figure 1.

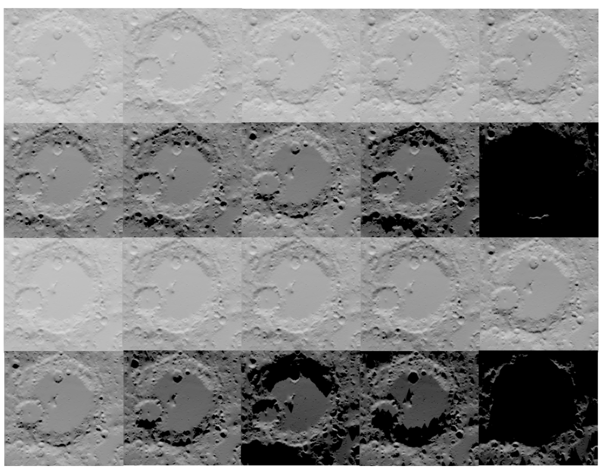

Figure 1: Albategnius crater 11.2°S 4.1°E as created using LTVT with LOLA64 DEM. Top 2 rows are the novel subset, bottom 2 rows are the training subset.

### Results

The experiment was completed 3 times for each patch size to obtain an average. All 10 images in each sample of the training subset were used to create the 'model' and the 'dictionary'. The results of which are presented in Table 2.

Like the CUReT experiment the 7x7 patch achieves a greater percentage classification rate than the rest with results declining over 7x7 patch sizes. This could be due to 7x7 patches being an ideal size to detect prominent textural information in a 200x200 pixel image. The results overall are lower than that of the CUReT experiment and to some extent this is expected as the images created by the LTVT are only ray traced images containing no albedo information. These results may be improved by using a higher resolution DEM, a greater number of phase angles and possibly smoothing the images to remove artifacts in the LOLA DEM.

| Patch Type | Average Classification % |
|---|---|
| 3x3 | 51.44 |
| 5x5 | 70.34 |
| 7x7 | 75.59 |
| 9x9 | 66.62 |

Table 2: LTVT Results: Table showing the % of correct classifications of novel images

### Summary

These early results demonstrate the possibility of classifying large amounts of imagery automatically, allowing researchers to explore quickly and easily for interesting features. To continue this work, a larger population of the LTVT samples is to be analysed with more phase angles along with exploring classifications based upon higher resolution LOLA data and geology maps.

### References


[1] N. Staab. Lunar Reconnaissance Orbiter Camera releases science data from first six months. March 2010. URL http://sese.asu.edu/node/751.

[2] M. Varma and A. Zisserman. Classifying images of materials: Achieving viewpoint and illumination independence. In *Proc of the 7th European Conf on Comp Vis*, volume 3, pages 255–271, May 2002.

[3] T. Leung and J. Malik. Representing and recognizing the visual appearance of materials using three-dimensional textons. *Int. J. of Comp. Vis*, 43:29–44, 2001.

[4] K.J. et al Dana. Reflectance and Texture of Real World Surfaces. Technical report, 1996.

[5] M. Varma and A. Zisserman. Texture classification: Are filter banks necessary? In *Proc IEEE Conf on Comp Vis and Pattern Recognition*, volume 2, pages 691–698, June 2003.

[6] S. Lloyd. Least squares quantization in PCM. In *IEEE Trans on Information Theory*, volume 28(2), pages 129–137, March 1982.

[7] D. M. F. Chapman. The Lunar-X Files: A Fleeting Vision near the Crater Werner. *JRASC*, 101:51–+, April 2007.

[8] H. et al Riris. The Lunar Orbiter Laser Altimeter (LOLA) on NASAs Lunar Reconnaissance Orbiter (LRO) Mission. In *Proc. SPIE*, volume 6555, page 65550I, May 2007.