

## 1 - Introduction

Automated methods for dealing with large amounts of image data can save researchers a great deal of time. However computers often have trouble comparing similar images viewed from different view and illumination conditions (phase angle). The work presented in this poster demonstrates a method to automatically classify and visualise large amounts of image data as well as providing a solution to issues of view and illumination angles when viewing remotely sensed imagery.

## 2 - Method

The 'texton' techniques first described in [1] and later [2] requires a training phase and a classification phase, therefore two sets of data are required. A training 'model' and 'texton' 'dictionary' are created in the training phases.

Patches are extracted from each image in the training set, row ordered and aggregated to be clustered using the K-Means method [3]. These clusters are known as 'textons' and form a 'model' that comparisons can be made with.

To create the 'dictionary', patches are extracted from the training set of images. The euclidean distance from each patch to the closest 'texton' in the 'model' is recorded by incrementing a histogram. These training histograms are stored and form a 'dictionary' for comparison with a 'novel' texture using  $\chi^2$ .

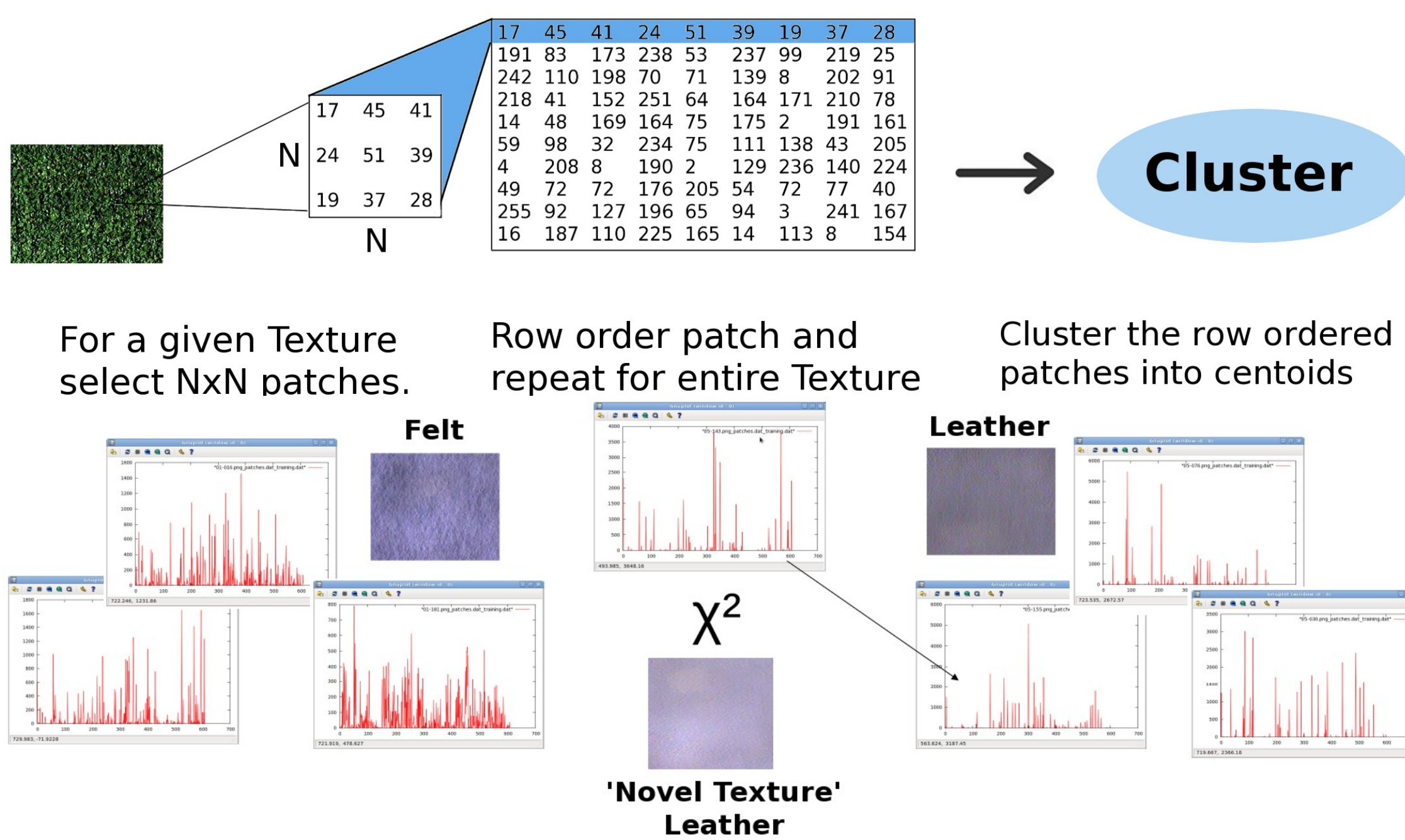


Figure 1: Pictorial view of the 'texton' method [2] as described in Section 2

## 3 - 'Texton' Performance

The performance of the method describe is examined using the CURET database [4] of textures. 61 textures are imaged at 92 different phase angles. Each image is 200x200 pixels. These are split into two disjointed sets each containing 46 images for each texture. These images are ordered in relation to their phase angle and are split evenly by selecting every other image for training, leaving the rest for classification.

Once a model is created from the training set, 'novel' images are randomly selected 50,000 times from the classification set, counting the percentage of correct classifications. This process is completed three times for each patch size to obtain an average. The results are displayed in Table 1.

Patch Type	Average Classification %
3x3	90.9
5x5	93.5
7x7	93.6
9x9	93.2

Table 1: Results from CURET experiment showing percentage of correct classifications

The results in Table 1 demonstrate a high percentage classification (~93%) of the CURET database. As observed by [2] the 7x7 patch size provides a superior classification for 200x200 pixel images.

## 4 - Crater Experiment and Performance

Thirty craters are simulated from the LOLA64 DEM using the Lunar Terminator Visualisation Tool (LTVT) [5] with a solar azimuth of 0° and 180°, each with an elevation 0-45° in 5° increments in relation to the center of the crater (see Figure 2). No albedo overlay is used to create these images. These are evenly split into two sets for training and classification and the whole experiment is run as described in Section 3. Therresults are displayed in Table 2.

As discovered in Section 3, the 7x7 patch produced the best results, however not as well as those presented in Section 3 (Table 1). This is largely due to the crater images containing no albedo information, only that which is simulated by the LTVT ray tracing model.

Patch Type	Average Classification %
3x3	51.4
5x5	70.3
7x7	75.5
9x9	66.6

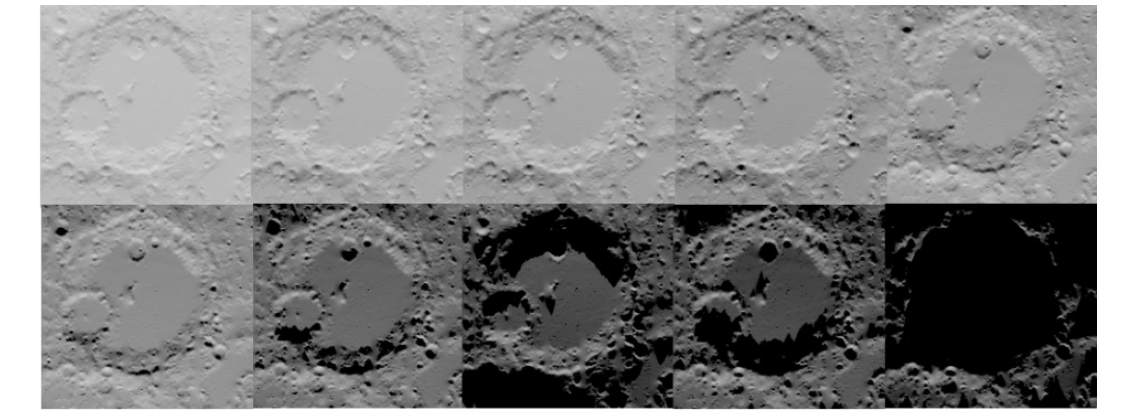


Table 2: Results from the LTVT Figure 2: Albatengnius crater 11.2° S experiment showing the percentage 4.1° E as created using LTVT with LOLA64 DEM.

## 5 - Lunar taxonomy of textures

Given a large image data set, a hierarchical structure of similarity may be expressed as a taxonomy to provide a visual representation of similar features. To demonstrate this, 200x200 pixel samples are extracted from thirty LROC-NAC images. Using the method describe in Section 2, the closest two textures are grouped. This is repeated until only one group remains (Figure 3).

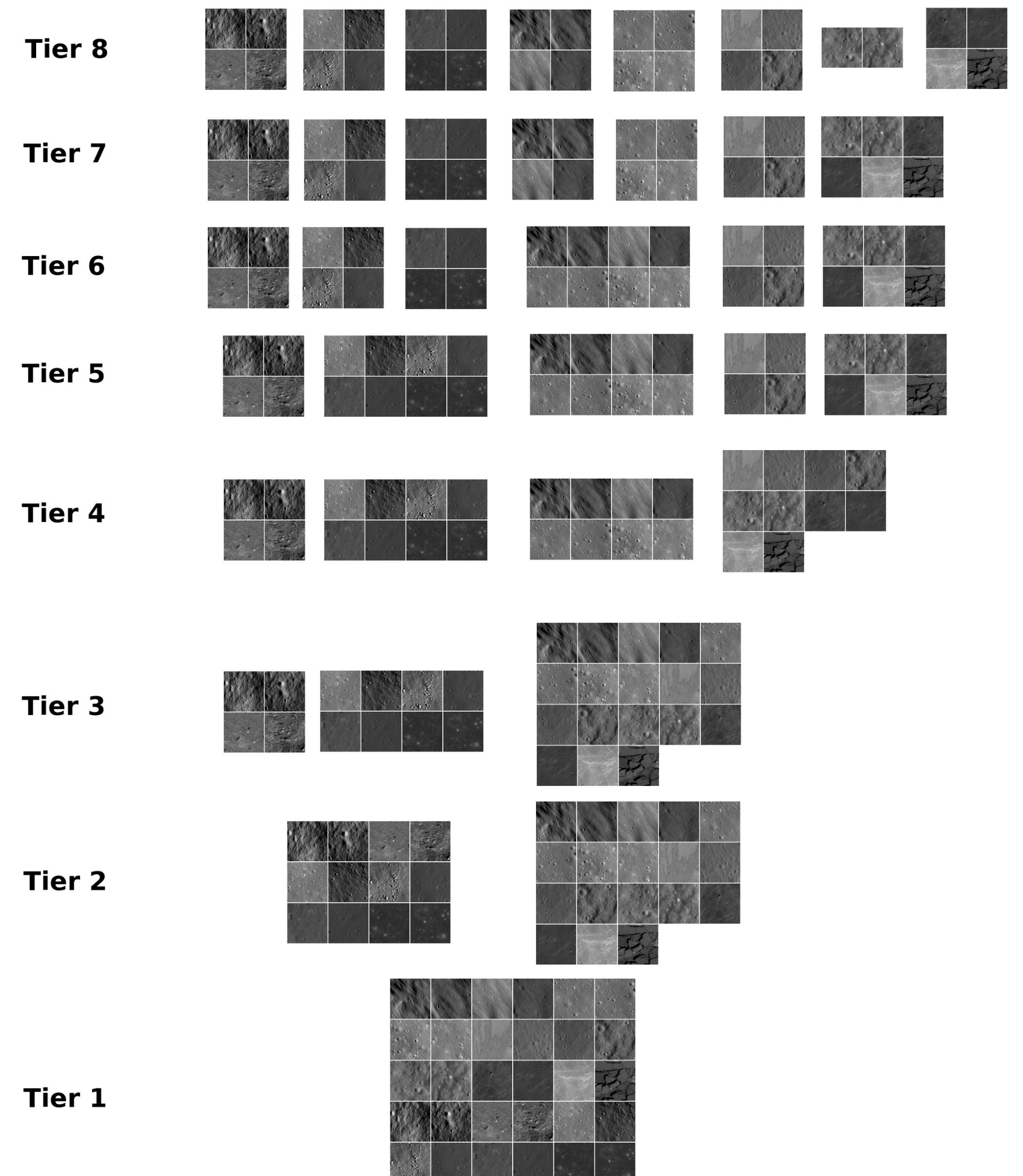


Figure 3: Final eight iterations of a taxonomy merging, using thirty LROC-NAC samples of texture.

Progressive mergers of similar textures are displayed from tier 8-1 to create a single group at tier 1 (known as the root node). This provides an ordered structure of similarity based on texture.

## Summary

The results produced in Section 3 and 4 demonstrate the potential for automated classification of large amounts of data. The lower correct classification percentage when using simulated craters in Section 4 (Table 2) is attributed to the lack of albedo information. This can be overcome by using satellite or ground based imagery under varying view and illumination conditions provided the model is sufficiently trained. Section 5 expands upon Section 2 to provide a method for viewing large amounts of image data based upon texture similarity, assisting researchers to search for interesting features within the imagery.

## References

- [1] 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.
- [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.
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- [4] K.J. et al Dana. *Reflectance and Texture of Real World Surfaces*. Technical report, 1996.
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