Automated Texture Classification and Landform Taxonomy for Populating a GIS

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Summary

Gibbens (2008) presents a methodology for assisting humans with analysing large amounts of image data. Split into four major sections, namely pre-processing, segmentation, region modelling and taxonomy creation (Figure 1a), each one can be implemented individually. With some success Gibbens demonstrates the methodology using several segmentation techniques, such as scale-spaces with blob detection and manual hand marked regions with expert consensus, along with a modified Texton approach for region modelling. This paper reviews the techniques employed by Gibbens, highlighting where improvements can be made as well as presenting the work conducted so far and discussing the development over the next two years.

Introduction

Image processing and classification is an important part of analysis in many fields of scientific research. The field of remote sensing uses vast amounts of image data from multiple sources, such as satellites or aerial photography, to monitor the earth. As technology improves allowing higher resolution imagery to be obtained, there is a need to improve the methods of organising large sets of image data. Despite humans ability to interpret imagery, we are unable to analyse large data sets quickly or accurately (Baddeley, 1997).

Gibbens (2008) presents a methodology which outlines several steps that should be taken to create an end-to-end system that assists humans to analyse large sets of image data (Figure 1a). This is based upon the idea of undirected browsing, (Marchionini, 1995) which allows the user to explore a dataset in an efficient manner. Several techniques are implemented to demonstrate this methodology to some success.

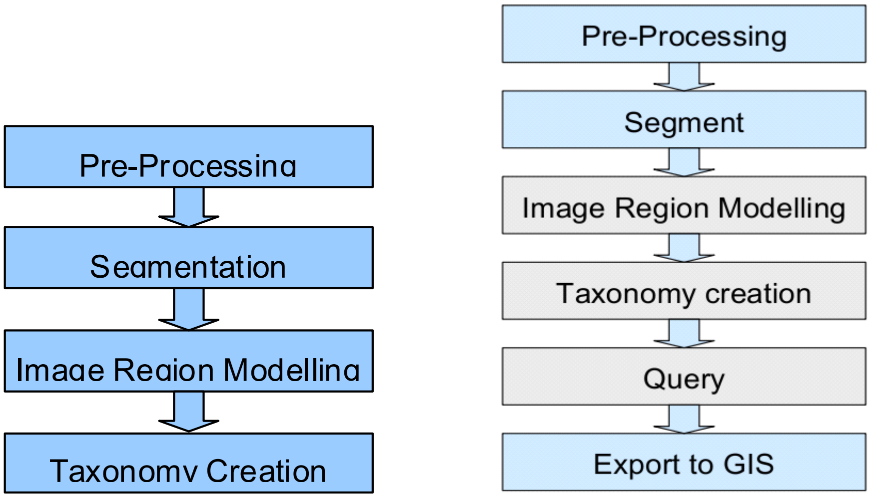

Figure 1. (a) Left: Flow Chart showing Gibbens' (2008) methodology (b) Right: Flow Chart showing extension to Gibbens' methodology, blue indicating where work is currently under way and white indicating where work is to begin.

This paper reviews the PhD research of Gibbens, outlining the strengths and weaknesses of the implementation. It then details work in progress to improve upon the methodology and create an enhanced image analysis tool.

Review

Methodology

Gibbens' (2008) methodology involves image region modelling techniques that are used on segmented imagery in order to create a hierarchical data structure for the display of large quantities of self similar landforms and texture. This methodology can be implemented using various approaches or algorithms at each step. Several such variations are presented, along with results, which demonstrate the potential of the method.

Firstly a series of regions, or segments, were created from an image. This was performed through different experimental approaches such as manually marking out regions, or using automated algorithms. However image segmentation is a difficult task and is largely dependent upon the purpose of segmentation which ultimately influences the whole system (Munoz *et al.*, 2003; Pal *et al.*, 1993). Once one has a series of regions, a description of each region is required in order to assess similarity. This description is obtained by producing a computationally tractable model that is applicable to heterogeneous image data. Many such models exist that analyse properties such as shape (Carson *et al*., 1997) or texture (Picard *et al*., 1993). The Texton approach introduced by Caelli and Julesz (1978), and made operational by Leung and Malik (2001), provides such a model.

In order to mitigate against the traditional reliance upon a pre-trained texture dictionary, as used in Leung and Malik (2001), a weighted Texton model (WTexton) was written (Gibbens, 2008). Unlike the standard Texton approach which compares the vector quantized filter responses of a population of regions to the pre-trained dictionary (e.g. the CUReT textural database (Dana and Nayar, 1999)), a WTexton identifies a small set of filter representative responses from the population. This was achieved by using a cluster analysis methodology such as K-mediod or agglomerative clustering, and results in the creation of a Texton set which was then compared to other sets without the need of a pre-trained dictionary.

There is much research available which discuss the optimal way that humans can view large quantities of image data (Bhatia, 2005). A taxonomy is a way that one can structure objects within an image in a meaningful way. Hierarchical clustering, such as the agglomerative clustering technique, provides a level of similarity as a series of subsets. A taxonomy of image regions is created thus aiding undirected browsing.

Experiments

In order to demonstrate the methodology outlined above, two planetary image mosaic datasets were used with the WTexton approach to model the image regions and create a taxonomy. Both fully automated and hand marked consensus methods were used to segment the image data which produced a varying quality of results, thus demonstrating the importance of image segmentation in this methodology.

Using map projected image data collected by the Clementine lunar spacecraft (Nozette *et al*., 1994), a series of crater sub images were extracted using the NASA lunar crater database (Blue, 2004). The crater database provides the diameter and crater centre location from which rectangular regions of enclosure can be used as pseudo segmentation. This technique allows image segmentation to be the closest to 'ground truth' that we can hope to obtain at the moment, thus demonstrating implementation of other steps in the methodology, such as the image region modelling and taxonomy creation.

The Mars Orbital Camera (MOC) (Caplinger *et al*., 1999) instrument aboard the Mars Global Surveyor (MGS) collected approximately 365 GB of uncompressed hi-resolution (down to ~0.5m/pixel) image data. Two methods of segmentation were used for this dataset. Firstly a public consensus method which asks on-line users to manually segment images, was used to produce 6842 regions from 200 selected 800 x 600 (pixel) image samples. Secondly, Lindeberg's (1994) method of automatically extracting features was also used and compared to the public consensus segmentation. This involved the generation of linear scale space using a Gaussian blurring filter followed by a 'blob-detection' algorithm to extract the dominant features.

Results and validation

The taxonomy created using the Clementine Lunar Mosaic produced visually compelling results, displaying craters with common features in the same cluster (figure 2). In order to assess the resulting taxonomy with a form of 'ground truth', the clustered craters were compared to the classification by Baldwin (1963). Baldwin produced a catalogue of 300 manually classified crater morphologies which were placed into one of five classes. Of those 300 craters within Baldwin's classification, 265 were found within the lunar crater database (Blue, 2004). When this comparison was made, 117 out of the 265 craters were classified adequately. However this can be explained by the fact that the Clementine imagery was taken at full Moon illumination (phase angle close to 0° at the equator) while the Baldwin classifications were made manually from nearside observations of the Moon, usually at low sun angle. It is well known that illumination angle alters the appearance of the surface considerably (Magee *et al.*, 2003), indicating not only that the Baldwin classification is inadequate for comparison in this situation, but also the difficulties involved with this type of imagery. Unfortunately there is no other lunar crater morphology classifications to compare against. The Clementine lunar data was successful in demonstrating WTexton approach of region modelling along with highlighting the difficulties inherent in imagery with multiple illumination angles.

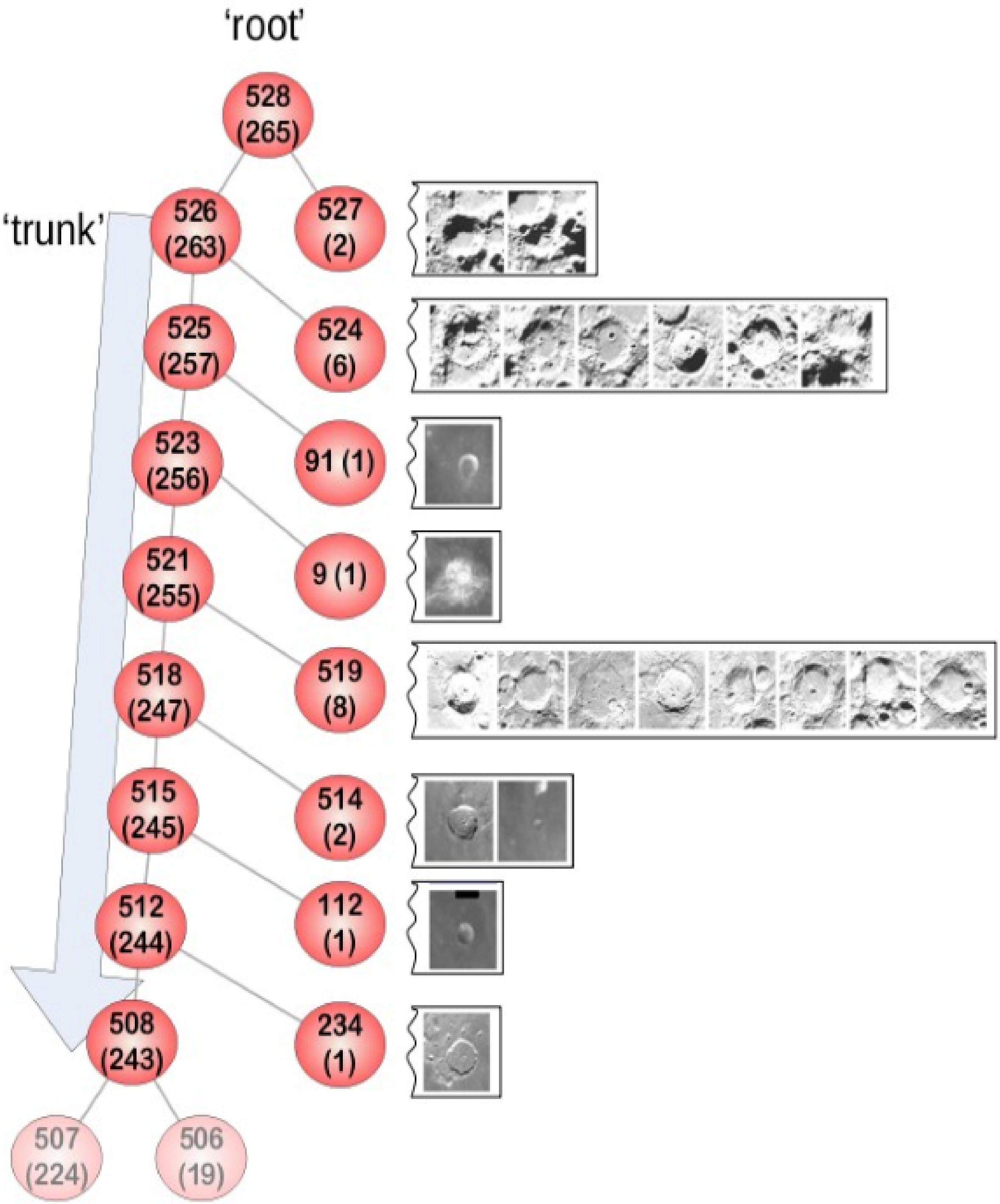

Figure 2. A Progression of clusters from the root of the taxonomy, cluster IDs shown with cluster size in parentheses.

The work conducted on the MOC data was able to show the inconsistencies between manual 'expert' segmentation when attempting to reach a consensus. The mean consensus between 14 scientists was just 22%, however this was possibly because scientist from different disciplines within the planetary science community were used. The work also drew attention to the limitations of the WTexton approach, namely that image regions must be larger than 1000 pixels, regions with less than 1000 pixels were discarded. Further more, the automatic segmentation method produced a larger number of regions containing less than 1000 pixels than consensus segmentation. From the 17754 regions produced automatically, only 7776 were used, resulting in 9978 (~56%) being discarded.

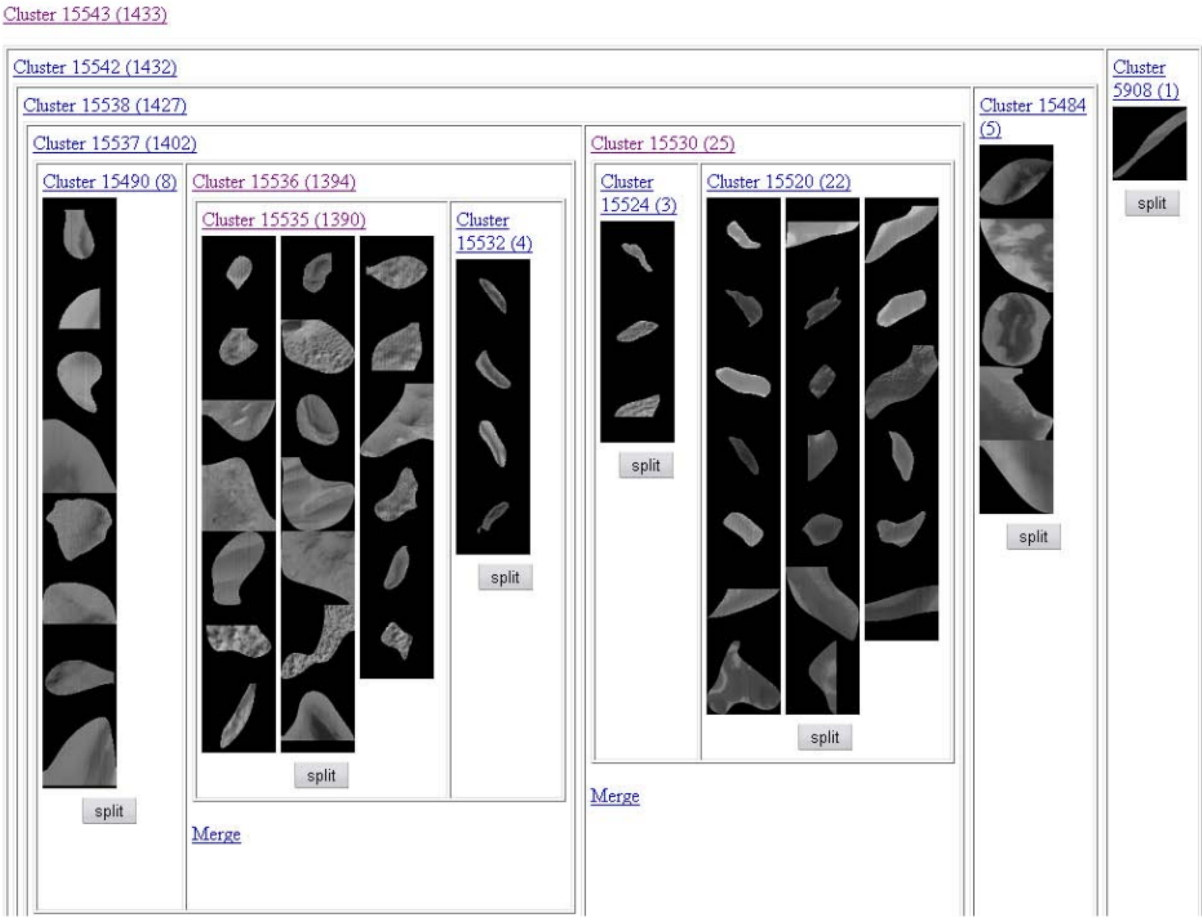

Figure 3. An example of the taxonomy created using automated segmentation of MOC data. Note that each cluster has a label and the cluster size is in parentheses.

The WTexon approach was able to create successfully a taxonomy from the remaining 7776 regions which, for example, accurately identify a significant number regions devoid of texture thus demonstrating a working taxonomy. Visually however, the regions within each cluster do not appear to be as uniform as those presented in the Clementine taxonomies, due largely to issues with the segmentation (Figure 3). This explains why the recall rate, the ratio of correctly identified features to total number of correct features, was so low in the automated method, namely less than 20%.

Improvements

Given the results presented in Section 2.3 it becomes apparent that the way an image is segmented affects the region modelling greatly. With a proven method of creating a taxonomy automatically using the WTexton approach the focus of further work will fall initially upon the improvement of the segmentation method. The first improvements to the segmentation algorithm have focused on the inclusion of terrestrial multi-band datasets as illustrated in figure 4. Simple techniques such as morphological operators can be used to great effect in the extraction of regions, however these often fail to cope with complex textures like ice flows or 'fuzzy-boundaries'. Work is currently under way to investigate an ideal texture based segmentation method which would provide suitable image regions for the WTexton based taxonomy using terrestrial imagery.

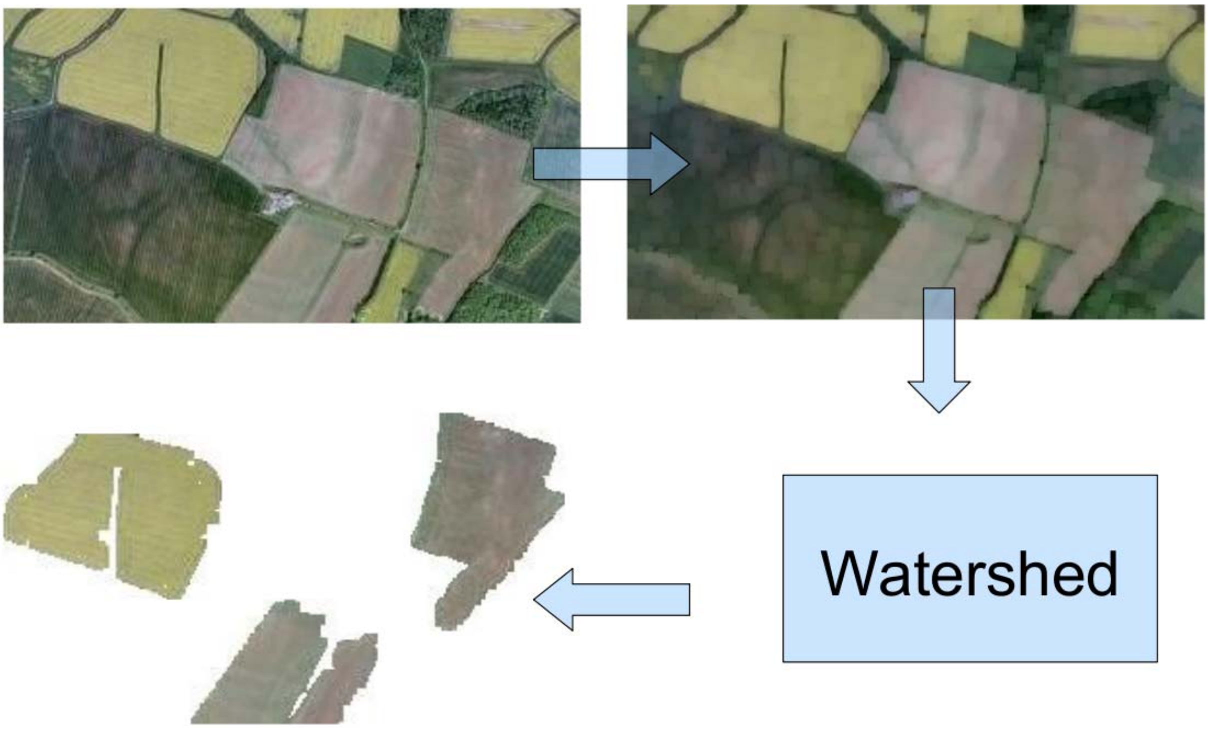

Figure 4. A two step segmentation process of farm land in the Derbyshire, UK, taken from aerial photography. A morphological close operator is followed by a watershed threshold.

Extending the use of the Gibbens' work has so far involved assessing region similarity and assigning an ID to similar regions which is then exported to a standard GeoTIFF format for use within a GIS. While this is not intended to be the final output of a taxonomy, it has allowed the development of a method to present taxonomy data within the GIS using a popular open file format.

Conclusion

A review of the work conducted by Gibbens has demonstrated the potential benefits of a system based upon his approach despite the need for improvements in certain areas. Image segmentation has been proven to play a very important role in the overall quality of a resulting taxonomy. Further work is to be conducted over the next two years in order to produce a viable method and implementation for dealing with large sets of planetary image data.

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References

BADDELEY, A., 1997. *Human Memory: Theory and Practice* (Hove: Psychology Press).

BALDWIN, R.B., 1963. *The Measure of the Moon* (Chicago: University of Chicago Press).

BHATIA, S., 2005. Hierarchical clustering for image databases. In *2005 IEEE International Conference on Electro Information Technology*, pp. 6–12.

BLUE, J., 2004. Gazetteer of planetary nomenclature. http://planetarynames.wr.usgs.gov/, 2004.

CAELLI, T.M., and JULEZ, B., 1978. Experiments in the visual perception of texture. *Biol. Cybernetics*, **28**: 167–175.

CAPLINGER, M.A., JENSEN, E., EDGETT, K., ELIASON, E.M., and GARCIA, P.A., 1999. An archive of MGS/MOC imaging data. In Lunar and Planetary Institute Conference Abstracts, Vol. 30 of Lunar and Planetary Institute Conference Abstracts, page 1659+.

CARSON, C., BELONGIE, S., GREENSPAN, H., and MALIK, J., 1997. Region-based image querying. In *Proceedings of the 1997 Workshop on Content-Based Access of Image and Video Libraries (CBAIVL '97)*, p. 42. IEEE Computer Society, 1997.

DANA, K.J., and NAYAR, S., 1999. Correlation model for 3d texture. In *International Conference on Computer Vision*, pp. 1061–1067.

FAYYAD, U.M., 1996. Data Mining and Knowledge Discovery: Making Sense Out of Data. *IEEE Intelligent Systems*, **11**(5): 20-25.

GIBBENS, M., 2008. Taxonomies for Image Set Analysis. PhD thesis. University of Nottingham, UK.

LINDEBERG, T., 1994. *Scale-Space Theory in Computer Vision* (Dordrecht: Kluwer Academic Publishing), pp. 423.

LEUNG, T.K., and MALIK, J., 2001. Representing and recognizing the visual appearance of materials using three-dimensional textons. *International Journal of Computer Vision*, **43**: 29–44.

MAGEE, M., CHAPMAN, C.R., DELLENBACK, S.W., ENKE, B., MERLINE, W.J., and RIGNEY, M.P., 2003. Automated identification of Martian craters using image processing. *Lunar and Planetary Science Conference, Houston, US, March 2003.*

MARCHIONINI, G.M., 1995. *Information Seeking in Electronic Environments* (Cambridge: University Press).

MUNOZ, X., FREIXENET, J., CUFI, X., and MARTI, J., 2003. Strategies for Image Segmentation Combining Region and Boundary Information. *Pattern Recognition Letters*, **24**: 375-392.

NOZETTE, S., *et al.*, 1994. The Clementine Mission to the Moon: Scientific overview. *Science*, **266**: 1835-1839.

PAL, N.R., and PAL, S.K., 1993. A review of image segmentation techniques. *Pattern Recognition*, **26**(9): 1277-1294.

PICARD, R.W., and KABIR, T, 1993. Finding similar patterns in large image database. *Proc. IEEE ICASSP Conference*, **5**: 161–164.