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Automated Quantitative Planetary Measurements

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Abstract

Despite numerous attempts to automate the process of analysing planetary images, none have been widely adopted. Instead, some researchers prefer to out-source large scale processing tasks to Citizen Science projects [1]. We believe that the lack of uptake in fully automated methods is not due to performance levels, but the omission of an error theory capable of providing measurements within predictable accuracies. Here, we outline our work towards a flexible pattern recognition system for extracting scientifically useful quantitative measurements from planetary images, providing maximum likelihood measurement estimates accompanied by clear error predictions (in the form of measurement covariances) and a goodness-of-fit indicator. We include encouraging results from Monte-Carlo data and synthetic Martian images derived from HiRISE [2] datasets.

1. Introduction

Our automated planetary image analysis method consists of: a supervised learning system using linear Poisson histogram models of exemplar terrains; a detailed error theory which computes measurement covariances via the application of error propagation; and a model goodness-of-fit using a chi-squared per degree of freedom test for Poisson histogram data.

1.1 Measurements from histograms

Incoming images are encoded as texture histograms by grouping together connected BRIEF-like [3] patches and recording their frequencies. During training, linear models of exemplar terrains are generated using an Independent Component Analysis based upon Likelihood which is optimised using an Expectation Maximisation (EM) algorithm. Surface area measurements (from which other measurements can be derived) are subsequently estimated by fitting the trained models, via EM, to terrain histograms computed for new incoming images. Model weighing parameters can then be converted to surface area measurements by scaling with BRIEF patch sizes.

1.2 Measurement covariances

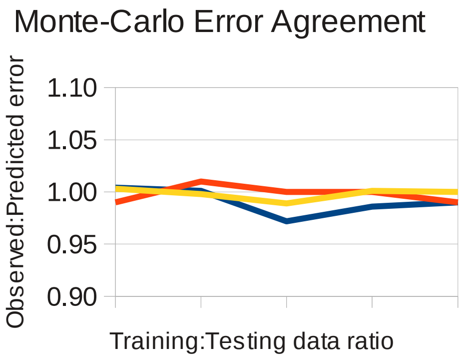
The stability of surface area measurements is computed by considering how noise in training data and noise in incoming data affects estimated model parameters. This is done via error propagation [4] which approximates measurement perturbations by computing the derivatives of model weights with respect to the sources of error. The sources of error are assumed to be independent Poisson sampling noise in training and testing histogram bins.

1.1 Goodness-of-fit

Problems with an analysis (e.g. unfamiliar terrains or outliers) can be identified using a chi-squared per degree of freedom function [4]. The residuals between modelled and observed histograms, which are Poisson, can be made to better approximate a Gaussian (even for small quantities) with a square-root transform, then a standard chi-squared per degree of freedom test can be applied.

2. Monte-Carlo and Martian data

In order to demonstrate proof of concept, large amounts of simulated terrain histograms were generated for a range of distributions and quantities of data, from which area measurements and errors were estimated. This was done using synthetic Martian images composed from varying quantities of 30 distinctive terrains selected from HiRISE data. These textures were smoothly composited, with additional noise to generate unlimited independent ground truth. The aim was to corroborate predicted errors by means of comparison to empirically observed error distributions, thereby confirming that measurements could be made within theoretically estimated accuracies. Figure 1 confirms error predictions for Monte-Carlo data and shows that error predictions for Martian data are almost within practical ranges for real applications. Figure 2 shows that high levels of measurement accuracy can be attained on Martian data, with surface areas estimated to within a couple of percent of ground truth values. Figure 3 shows an example composite Martian terrain used during testing.



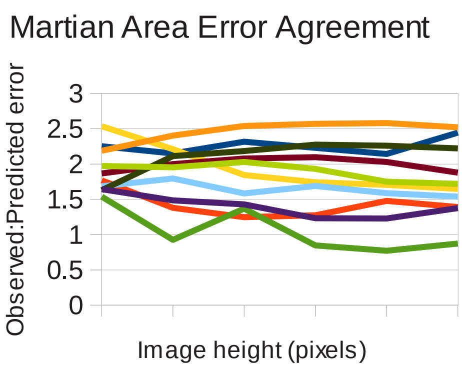


Figure 1: Top, ratio of observed to predicted errors on Monte-Carlo histograms. Bottom, area error ratios plotted against image size for 10 groups of 3 Martian terrains for composite images of width (2048 pixels)

3. Conclusions

Our automated approach for planetary image analysis is unique amongst previously proposed methods and (to our knowledge) the only one capable of producing data specific error estimates. Also, our method is the only one to provide a goodness-of-fit function as a means of identifying problematic incoming data. Testing on Martian data reveals that error predictions on real images could be improved, perhaps by the use of a calibrated DOF scaling, but estimates achieved within a factor of 2 are sufficient for preventing over-interpretation of measurements and hence our method is approaching practical utility.

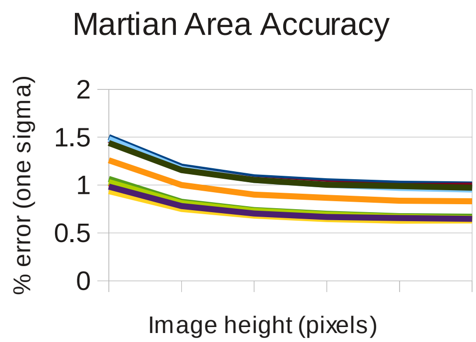


Figure 2: Percentage measurement accuracies attainable on Martian surface area measurements.

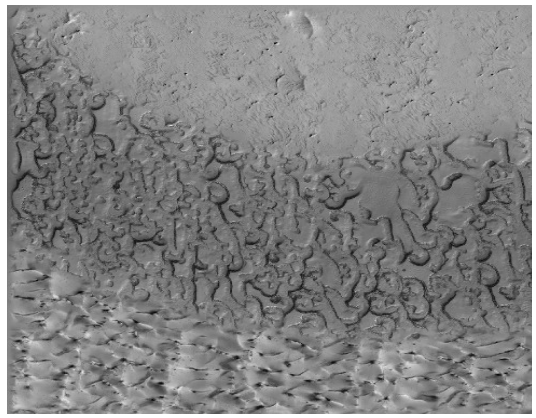


Figure 3: Example composite Martian image.

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