INVESTIGATING THE POSSIBILITY OF SUPER-RESOLUTION RECONSTRUCTION OF LRO DIVINER DATA. K.-M. Aye[1], B. T. Greenhagen[2] and J. P. Williams[3], [1]Laboratory for Atmospheric and Space Physics, University of Colorado at Boulder, 1234 Innovation Drive, Boulder, CO 80303, USA (michael.aye@colorado.edu), [2]Johns Hopkins Applied Physics Laboratory, Laurel MD USA, [3]Earth, Planetary, and Space Sciences, UCLA, Los Angeles, CA USA.

Introduction: We are investigating the possibility of creating higher resolution products of LRO Diviner [1] data for special areas of interest and sufficient coverage following a standard super-resolution approach, aligned with the work of Hughes and Ramsey [2], who applied these techniques successfully to ASTER and THEMIS data.

Diviner instrument: The LRO Diviner instrument is a multi-channel visual, mid-IR to thermal (far) IR spectrometer, using thermopile detectors to measure lunar IR surface radiation. It has 2 visual channels of 2 different sensitivities to cover all observation scenarios, 3 mid-IR channels from 7.8 to 8.55 for mineralogy, and 4 thermal channels between 13 and 400 micron. Each channel consists of a row of 21 detectors that are scanning the surface, with the row being orthogonal to the flight direction. Due to the thermal nature of the detectors, their response time and spacecraft motion, the effective field of view (EFOV) is asymmetric (ellipsoidal [3]), with elongation in the flight direction. The integration time is 128 ms and the exponential thermal detector response time 110 ms [1], with a ground speed of approx. 1.66 km/s. Broadening of this in-track field of view varies linearly with orbital altitude, being relatively larger at lower altitudes, with no broadening of the FOV cross track apart from the inherent IFOV of each detector.

The current procedure for taking these changes of the EFOV between different observations into account is a continuous Monte-Carlo simulation during the data-reduction pipeline that simulates the observation on top of high-resolution topography data from the LRO laser altimeter LOLA, a procedure that is called "pfootprint" in our pipelines. The disadvantage of pfootprint is that it slows down the reduction immensely depending on the required quality of the result and it can blur or smoothen the data a bit, while an advantage being it better aligns the Diviner channels and fixes aliasing problems when binning data [3].

Super-resolution is a process for obtaining a spatial resolution greater than that of the actual, original (or native) resolution of the data. Any source of extra information can be used to statistically improve the ground knowledge. This can either be data from other wavelengths, or multiple overlapping observations of the same ground with slight differences of the ground spot observed due to pointing differences. The most commonly applied technique, according to [2] is pan-sharpening, where a higher resolution panchromatic channel is used to sharpen lower-res multi-spectral channel. A further development is the Multisensor Multi-resolution Technique (MMT, [4]) works with multi-spectral data at both higher and lower spatial resolutions [2].

Hughes and Ramsey [2] have applied this technique to the Earth-orbiting "Advanced Spaceborn Thermal Emission and Reflection Radiometer" (ASTER) and the Mars-orbiting Thermal Emission Imaging System (THEMIS), with the aim of producing radiometrically-accurate but improved resolution data in the thermal infrared. Our effort is guided by their success [2].

An essential part of most of the techniques used is a good knowledge of the point spread function of the instrument, which has been measured in detail in the lab [1].

Algorithm: The algorithm described by [2] consists of 5 steps:

1. Convolution of high resolution data with the PSF. In Diviner we have a the visual and 8 micron mineralogy channels having a higher spatial resolution than the thermal channels (up to 33 % better).

2. Identifying homogenous pixels. This is actually an interesting issue for Diviner as we have previously seen groups of pixels more homogenous than others, presumably caused by more or less thermal cross-talk, as discussed in [1]. Edge pixels are always assumed to be non-homogeneous in this technique due to the lack of neighboring pixels supporting that categorization.

3. A spectral clustering tree. Clustering is a means of grouping together the data measured in multiple ways, such as spectral bands, such that each cluster contains members are more similar to each other than to other data [2]. The distance measurement applied for this clustering is the so called Mahalonobis distance (MD, instead of the standard Euclidian distance). The MD can be thought of as equivalent to the Euclidian distance for multi-dimensional data, except that it takes into account the differences of scale along each axis and discounts dimensions that are highly correlated [2]. Because of a stark development of clustering techniques in recent years, we expect to explore other newer methods for this sub-task.

4. Assignment of super-resolved values. During this step, initial DN values are assigned to each super-resolved pixel. These values are selected from both the data tree created in Step 3 and from nearby homogeneous pixels. A parameter in this step is a search radius in the low resolution data to be matched for similarity.

5. Radiometric correction. The newly super-resolved pixels are degraded back to the original resolution using the PSF and a correction factor data base is being created to be applied for each final pixel.

LRO specific adaptations: The LRO orbit was changed to a higher orbit after several years. As discussed above, the smearing effect is of lower relative importance at higher altitudes, while the geometric resolution is obviously worse. We will need to investigate if observations of these different orbit altitudes can be used as additional data-sets of different resolution for the suggested algorithm, instead of just using different wavelengths. We will discuss our proposed approach and progress during the conference.

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