A SEMI-AUTOMATED DATA PIPELINE FOR CHARACTERIZING PRE-IMPACT TOPOGRAPHY RELEVANT TO LUNAR RAY GEOMETRY L. Powers ${ }^{1}$, J. Partee ${ }^{1}$, K. S. Martin-Wells ${ }^{1}$, ${ }^{1}$ Ursinus College (Pfahler Hall, 601 E. Main Street, Collegeville, PA 19426, kmartinwells@ursinus.edu).

Introduction: Crater rays are an important record of the transport and mixing of materials on the lunar surface. Over the years, investigations of their formation and preservation have yielded important insights into the impact cratering process and the evolution of the lunar surface [e.g., 1-3]. Until recently, however, the source of the asymmetry of prominent crater rays was not well-understood. Recent work by Sabuwala et al. [2018] showed that the number of prominent rays produced by laboratory impacts into granular targets was determined by the scale of undulations in the pre-impact topography relative to the size of the projectile [4]. Sabuwala et al. [2018] validated their experimental results with numerical simulations and compared the projectile diameters that were predicted by their method for the lunar craters Tycho and Kepler to those derived from scaling laws [4]. In this work, we seek to apply the method of Sabuwala et al. [2018] to a wider sample of lunar craters [5]. However, due to the large number of elevation profiles that must be extracted and analyzed in order to create a reasonable statistical proxy for the pre-impact topography of an existing lunar crater, we present our progress on a semi-automated pipeline that has greatly reduced the time needed to conduct this work.

Background and Methods: Sabuwala et al. [2018] showed that the number of prominent rays observed for a crater is determined by the number of prominent valleys that are encountered by the perimeter of the projectile at impact [4]. Assuming a spherical projectile and normal incidence, this perimeter is a circle with the projectile diameter, $\mathrm{D}_{\text {proj }}$. If an elevation profile of the pre-impact topography is taken along a circle of $D_{\text {proj }}$ that is centered on the point of impact, then the number of prominent minima, $\mathrm{N}_{\mathrm{v}}$, in this elevation profile should be equal to the number of prominent rays, $\mathrm{N}_{\text {rays }}$, of the resulting crater [4].

Therefore, an estimate of $\mathrm{D}_{\text {proj }}$ for an existing crater can be measured by taking circular elevation profiles at varying hypothetical values of $\mathrm{D}_{\text {proj }}$ and extracting the associated number of prominent minima, $\mathrm{N}_{\mathrm{v}}$. By plotting $D_{\text {proj }}$ vs. $N_{v}$, the value of $D_{\text {proj }}$ that matches $\mathrm{N}_{\text {rays }}=\mathrm{N}_{\mathrm{v}}$ can be extracted from the resulting curve [4]. However, for an existing lunar crater, it is not possible to sample the pre-impact topography at the point of impact because this topography was destroyed by the subsequent crater excavation. Following the method of Sabuwala et al. [2018], we use 75 points distributed
within an annulus surrounding the resulting crater's continuous ejecta blanket (with an inner radius of 1.5 and an outer radius of 2 crater radii) as a statistical proxy for the topography of the pre-impact surface [4].

For each of the craters within our study, we selected 75 regions from within this annulus, each with dimensions of $10 \mathrm{~km} \times 10 \mathrm{~km}$. We defined nine circular elevation profiles for each of these 75 regions, corresponding to the perimeter of hypothetical projectiles ranging in size from $D_{\text {proj }}=2 \mathrm{~km}$ to 10 km at diameter increments of 1 km . We then extracted elevations from the LOLA 1024 ppd Numeric Elevation layer in JMARS, using points along the circular perimeters with a spacing of $747 \mathrm{~m}[6,7]$.

In our previous data collection method, the latitude and longitude for the points that make up each of the nine elevation profiles for each of the 75 analysis regions within the crater annulus were calculated and manually copied into shapefiles to load into JMARS. Once these shapefiles were loaded into JMARS as a single layer, we extracted the elevation from each point [5]. We then individually inverted each of the profiles in a spreadsheet so that the minima became maxima. This prepared each profile for the MATLAB findpeaks() function, which Sabuwala et al. [2018] used for their analysis. The inversion and transfer of this data from JMARS to MATLAB quickly became unwieldy, given the number of elevation profiles that we intended to process.

For this reason, we have developed a semiautomated data pipeline that reads in the elevation profiles that are extracted in JMARS and automatically identifies the number of prominent valleys in each profile. Run in batches, this pipeline can process all nine profiles for each of the 75 analysis regions from a single set of user commands. In the future, we also plan to automate the generation of the shapefiles that are used to extract the elevation profiles in JMARS. We will also automatically generate plots of $\mathrm{D}_{\text {proj }}$ vs. $\mathrm{N}_{\mathrm{v}}$, extract the best value of $\mathrm{D}_{\text {proj }}$ for each analysis region, and average these 75 values to produce an estimate of $\mathrm{D}_{\text {proj }}$ for each crater.

Details of the Data Pipeline: After extracting the elevation data from the JMARS shapefiles, our data pipeline averages adjacent points in each elevation profile. This averaging smooths the profile and helps to remove local minima that do not reflect prominent valleys. Future work will compare the smoothed and
unsmoothed profiles to assess any statical differences in the number of minima extracted. After averaging, the next stage in our data pipeline is to automatically extract the number of prominent minima from each profile.

First, we use the IDL function local_max_finder (which can be set to find either maxima or minima in a data series) to locate minima within the profile, regardless of their prominence. However, many of these candidate minima represent shallow dips in the local topography rather than truly prominent valleys. For this reason, we further characterize each candidate minimum in order to remove these "false valleys" from the automated analysis pipeline.

In order to remove false valleys that are shallow dips along larger-scale topographical slopes (such as a tiny divot along the interior of a larger crater wall), we define a parameter called walk-distance. If a topographic maximum is not encountered within the nearest datapoints as defined by walk-distance from the candidate minimum, then the candidate minimum is discarded as a false valley.

If topographic maxima are encountered within this walk-distance to either side of the candidate minimum, then three additional parameters are calculated. The first parameter is the slope of a hypothetical line that connects the topographical maxima to either side of the candidate minimum (Slope $=$ Elevation difference between maxima/Distance along the profile between maxima). The second parameter is the average of the elevation difference between the two maxima and the candidate minimum. We define this parameter as the depth of the candidate minimum. The third parameter is the distance along the profile between the two maxima. We define this parameter as the width of the candidate minimum.

The user defines the cut-off values for the walkdistance, slope, and a ratio of depth-to-width at the beginning of each pipeline run. In this manner, the degree of prominence of the minima which are kept as prominent valleys vs. those that are discarded as false valleys can be tuned. We are still in the process of determining the ideal values of these parameters in order to minimize the number of false valleys that are included in the final automated data extraction while identifying all of the truly prominent valleys in the elevation profiles.

Once we have extracted the number of prominent minima for each region, we will plot $\mathrm{D}_{\text {proj }}$ vs. $\mathrm{N}_{\mathrm{v}}$ for each proxy location to determine the value of $\mathrm{D}_{\text {proj }}$ that corresponds to $\mathrm{N}_{\mathrm{v}}=\mathrm{N}_{\text {rays. }}$. For Jackson crater, we take the number of rays as $\mathrm{N}_{\text {rays }}=12$ [8]. After determining the best value of $\mathrm{D}_{\text {proj }}$ for each of the 75 regions, we will average these 75 values to determine $D_{\text {proj }}$ for the
crater and compare this value to the projectile diameters that are estimated by scaling laws.

Conclusions: The semi-automated nature of our improved data analysis pipeline already greatly reduces our analysis time and makes the intended scope of this investigation feasible. In future work, we plan to further automate the creation of the JMARS shapefiles from which the elevation profiles are extracted, as well as automatically average the $D_{\text {proj }}$ values from each of the 75 regions before applying this method to a broad sample of lunar rayed craters.

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