Automated Feature Extraction and Hydrocode Modeling of Impact Related Structures on Mars: Preliminary Report. C. S. Plesko[1] , E. Asphaug[1], S. P. Brumby[2], and G. R. Gisler[2], [1]University of California, Santa Cruz, Earth Sciences Dept. cplesko@es.ucsc.edu, [2]Los Alamos National Laboratory.

Introduction: We have begun a systematic, combined modeling and observation effort to correlate Martian impact structures – craters and their regional aftermaths – to the impactors, impact processes and target geologies responsible. When the cratering process is modeled in 3D, so that azimuthal heterogeneity is accommodated, one can seek best-fits to regional or even global distributions of radial fractures, crater rays and secondary streamers.

We are pursuing this cratering work on two fronts, (1) using automated feature extraction techniques to identify the extensive impact-related features on Mars, and (2) leveraging these impact features through impact modeling (using the 3D SPH and SAGE hydrocodes) to tell us about the specific target response to impact, and hence Martian geology.

We are motivated to do this because the Mars data set is now rich with well-characterized impact features, many of them recent and detailed, and because azimuthal asymmetry in cratering has never been adequately modeled in this context. The asymmetry of crater ejecta (rays and secondary streamers) is probably related to the asymmetry of ejecta from catastrophic disruption events in asteroid disruption[1], a subject which also suggests that the delivery of meteorites from the surface of Mars may be easier to understand in 3D than in 2D.

Impact Structures: Keys to the subsurface geology of every cratered body can be found in the study of its impact structures. But interpretations of the cratering process on planets are diverse, and Mars is no exception. For example, there exists no consensus among crater geologists and modelers on the process of crater rebound. Despite decades of intensive research in this area, we must confess to a broad ignorance regarding how large craters form. The hypothesis of panspermia[2] – that planets can swap rocks via impact ejection and perhaps exchange the seeds of life – is supported by the SNC meteorites, but the process by which these rocks were ejected from Mars remains controversial[3,4] Vickery[5] first attempted to use crater secondaries (around Copernicus on the Moon, Lyot on Mars, and others) as "witness plates" of the size-velocity distribution of ejecta from a crater, since secondary distance from primary easily relates (on an airless body) to ejection velocity, and secondary diameter relates to ejecta fragment diameter. Asphaug[1] made use of this work to calibrate impact hydrocodes in a planetary setting, and used it to explain ejection of V-type asteroids from asteroid 4 Vesta. Vickery[5] together with her undergraduate assistants lost the secondary craters in the background population beyond a few crater radii, so that the fast "tail" of ejecta fragments (those most relevant to panspermia) remained uncharacterized. Bierhaus et al.[6] made use of the extraordinarily fresh ~26 km diameter impact structure Pwyll on Europa to characterize ejection patterns at global distances. Pwyll's secondaries were used by Moore, Asphaug, and others[7] to explore whether the crater formed in an ice shell over liquid water, or in solid ice, the distal secondaries and rays from Pwyll have yet to be fully exploited to constrain Europa's geology.

Mars, especially in the post-THEMIS era, opens up a treasure trove for planetary impact modelers. Notably, impact craters have been discovered on Mars to be accompanied by associated structures that extend for many hundreds of kilometers, including detailed ray patterns and secondary streamers. The most stunning example is the fresh crater of the Cerberus plains presented by McEwen et al. (2003)[8]. We are using automated feature detection software to map the extent and distribution of such structures by keying to the desired signature (e.g. ray patterns) in the multispectral THEMIS imagery.

Automated Feature Detection:

GENIE. Los Alamos National Laboratory's GENIE system[9] is an innovative machine learning software package using techniques from the fields of genetic algorithms[10, 11] and genetic programming[12] to construct custom feature extraction algorithms for remotely sensed imagery[13, 14]. It was developed to allow rapid development of image analysis software tools for multispectral and hyperspectral imagery in the context of Earth remote sensing[15]. GENIE is particularly well suited to exploratory analysis of multi-wavelength imagery for which spatial/textural as well as spectral signatures can help identify features of interest, as well as analysis of imagery for which there do not yet exist the detailed atmospheric models needed to turn at-sensor radiances into at-surface material properties (reflectances and emmissivities). This is precisely the case facing scientists carrying out initial analysis of high resolution THEMIS data.

Both the structure of the feature extraction algorithm, and the parameters of the individual image processing steps, are learned by the system. The format of an algorithm evolved by GENIE is human-readable code than can be analyzed to understand the

physical signatures of the feature of interest. The evolved algorithms combine spatial and spectral processing, and the system was designed to enable exploration of spatio-spectral image processing of novel datasets. This system has been shown to be effective in detecting complex spatio-spectral terrain features in multispectral and hyperspectral imagery, and has been successfully applied to a number of real-world problems, including analysis and mapping of ash/debris from the September 11 attack on New York City and analysis and mapping of the burn scar following the Los Alamos Cerro Grande wildfire[16].

GENIE begins by randomly generating a population of candidate image-processing algorithms from a collection of spectral and spatial/textural image processing operators, including local neighborhood statistics, texture measures, spectral band-math operations (e.g. ratios of bands), and gray-scale morphological filters with various shapes of structuring elements. Each candidate algorithm consists of a number of these image-processing operators, which together generate a vector of processed images in an intermediate, nonlinear feature space. These are combined using a Fisher linear discriminant to produce a single gray-scale result image in which bright pixels indicate the presence of the feature of interest. This gray-scale result is converted to a Boolean classification using an optimal threshold[17]. The parameters of the Fisher discriminant and threshold are based on training data provided by the human user via GENIE's graphical interface. Our fitness metric for evaluating candidate image-processing algorithms measures the total error rate (false positives and false negatives) calculated from the training data. After a fitness value has been assigned to every candidate algorithm less fit members of the population are discarded. A new population is generated by allowing the most fit members of the old population to reproduce with modification via the evolutionary operators of mutation and crossover. To ensure a monotonic increase in fitness the most fit individual in the current population is kept without modification (principle of elitism). This process of fitness evaluation and reproduction with modification is iterated until the population converges, or some desired level of classification performance is attained, or some user-specified limit on computational effort is reached (e.g., a limit on the number of candidate algorithms evaluated). This Boolean threshold on the best image processing algorithm returned by GENIE may be adjusted by the user to re-adjust the emphasis of detection rate (true positives) over false alarms and missed detections. There is often more than one solution to a particular feature extraction question, in which case the results of several different algorithms trained on the same training data may be combined to increase detection accuracy and lower false alarm rates[18].

Past Efforts. Past Mars-related GENIE efforts have focused on crater extraction in panchromatic Mars Orbiter Camera imagery. GENIE was able to generate algorithms that detect craters in images it was not trained on with 94% detection and 2% false alarm rates compared to a manual crater survey[19].

Applications to Impact Modeling. GENIE is an extremely powerful tool for extracting features from large numbers of images, and especially for multispectral data, which it can process more readily than a human analyst. We will use GENIE to explore relationships between impact related features which are obvious to a human analyst, and use them to search for less obvious features, such as crater ray material farther downrange of the impact than is immediately obvious to the analyst.

Hydrocode Modeling: GENIE provides the reduced data set to be reproduced with our impact models. We are using Smooth Particle Hydrodynamics (SPH) and the adaptive grid Eulerian hydrocode known as SAGE, both in 3D, to model the formation of the best-preserved crater structures on Mars, the goal being to match not only crater size and shape but also regional aftermath such as secondary crater fields, azimuthal asymmetries, and ejecta rays. Beginning with simple equations of state (e.g. basalt) and moving to sophisticated equations of state for candidate Martian geology (for example saturated versus dry alluvium over basalt) we shall establish initial conditions (target geologies) to be tested for each GENIE-derived data set.

SAGE and SPH: The SAGE code from Los Alamos National Laboratory and Science Applications International Corporation is a compressible Eulerian hydrodynamics code using continuous adaptive mesh refinement (AMR) for following discontinuities with a fine grid while treating the bulk of the simulation more coarsely. In previous work[20] we have used tabular equations of state for the atmosphere, water, oceanic crust, and mantle of Earth. We are porting to SAGE the revised ANEOS parameters as well as the sophisticated explicit-fracture treatment developed within the context of Smooth Particle Hydrodynamics (SPH)[21] for high strain rate fragmentation in planetary impacts. The two codes are based on very distinct numerical techniques (Eulerian AMR vs. gridless Lagrangian), and are therefore of complementary utility, with SAGE being useful for studying atmospheric interaction and SPH being better suited – at present, at least – for studying solid rock fragmentation effects.

Results: The first task is to use GENIE to extract feature signatures of impact, correlated to particular craters on Mars. We shall present our progress in this area, the fundamental goal being a basic set of well-characterized impact outcomes to be modeled with the hydrocodes. By treating each impact structure as a detailed aftermath – not just a crater diameter, for instance – we open up a new, careful, and detailed study of the Martian lithosphere and atmosphere.

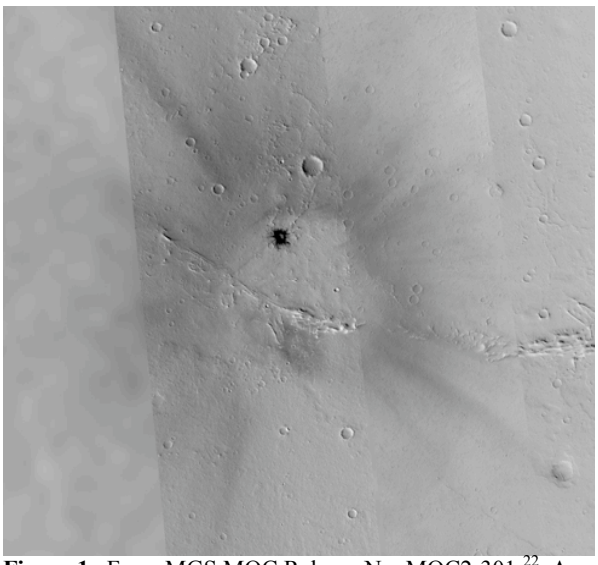

Figure 1. From MGS MOC Release No. MOC2-301.[22] A small, unnamed crater (~130 m diameter) is surrounded by a wealth of geophysical detail which can be exploited by the SAGE 3D hydrocode. It is clearly an oblique impact with an airburst followed by core penetration of the surface – perhaps a small comet with a rocky core? Both the structure of the impactor and the response of the Martian atmosphere can be modeled with SAGE's AMR capability. GENIE will search for similar levels of detail, generally hidden in visible imagery, in the THEMIS data sets, correlated to given impact craters. The goal is to produce several complete data sets, for varying sizes of craters, consisting of the crater itself, and the distribution of rays and secondaries.

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