COMPUTER MAPPING OF VALLEY NETWORKS ON MARS: AN OVERVIEW OF METHODS AND CHALLENGES. T. F. Stepinski[1] and W. Luo[2], [1]Lunar and Planetary Institute, 3600 Bay Area Blvd., Houston, TX 77058, tom@lpi.usra.edu, [2]Department of Geography, Northern Illinois University, DeKalb, IL 60115, wluo@niu.edu

Introduction: The valley networks (hereafter referred to as VN) are viewed as a key evidence that water once flowed over the Martian surface. The precise origin of VN is debatable because numerous detailed analyses of their geomorphic features yielded contradictory evidence with some features pointing to runoff erosion [1,2,3,4,5,6,7,8,9] while other favoring erosion by groundwater sapping [10,11,12,13,14]. In any case, a comprehensive map of VN is a prerequisite for all studies addressing their origin. The first global map was produced by Carr [15,16] from Viking-based images covering ±65° of latitude. The Carr map contains over ~ 800 networks with ~8000 branches; taken globally it depicts an immature drainage. However, new, higher resolution images reveal more valleys and call for an update to the global map of VN. One update effort [17], currently underway, is based on 100 m/pixel daytime IR THEMIS images. The preliminary results [17] indicate > 4 times as many valleys having ~ 2.5 times greater length than what has been mapped by Carr.

An alternative approach to updating the global map of VN is to use automated techniques that identify valleys by parsing the data by a computer algorithm. Advantages of such auto-mapping are: 1) low cost of acquisition, 2) consistent, objective results, 3) scalability. This last feature allows for efficient mapping of VN from higher resolution data as it becomes available. For data with fine enough resolution auto-mapping becomes the only viable option as the cost of manual mapping becomes prohibitively high. The shortcomings of auto-mapping are: 1) valley detection not on par with human cognition, 2) it requires high quality topographic data.

High resolution data describing Martian surface is mostly in the form of images. Although auto-mapping of valleys from imagery data was researched [18], the most reliable methods require digital elevation model (DEM) data. For Mars the global DEM (MOLA Mission Experiment Gridded Data Record or MEGDR) is available [19] with the spatial resolution of 1/128 degrees/pixel or about 463 m/pixel at the equator. Higher resolution DEMs (as high as 50 meters/pixel) are available for selected regions on Mars by processing stereo images taken by the High Resolution Stereo Camera (HRSC). The resolution of these datasets put an effective limit on a resolution of auto-generated maps of VN.

Methods: Majority of existing [20,21,22,23] auto-mappings of VN over selected regions on Mars were done using some variant of the D8 algorithm [24]. The D8 algorithm is a well-known GIS function, designed to take a DEM and compute an expected hydrologic network. Water is assumed to drain from each cell of the DEM to the lowest of the cell's eight neighbors. Water is allowed to accumulate downhill, and when the volume passing through a cell exceeds a certain threshold a channel is predicted. In variants of the D8 algorithm channel incision prediction is based on different models: stream order [25], volume and slope [26], and volume and stream length [27]. Regardless of a model, the D8 algorithm always delineates a dissection pattern having roughly an uniform drainage density [28]. Thus, despite being the most popular, the D8 algorithm produces spurious maps when applied to non-uniformly dissected terrain like the surface of Mars. In order to perform a global or even regional auto-mapping of VN on Martian surface a computer algorithm that detects valleys directly, rather than predicting them from a model, needs to be employed.

We have developed [29] an algorithm for a direct detection of VN from a DEM that does not rely on flow directions and channelization models; instead it detects incisions straight off terrain morphology. It identifies concave upward (U-shape) topographic features as valleys. The U-shaped features are associated with the cells in a DEM having positive topographic curvature. Special care needs to be taken to minimize noise while numerically calculating a curvature. In [29] this challenge was addressed by calculating curvature analytically for each cell in the DEM using a polynomial approximation to the local patch of the surface. The positive values of the curvature flag segments of U-shaped terrain and a series of image processing transformations turn these segments into a map of VN. In preparation for global mapping of VN we have applied our algorithm to two quadrangles, Mare Tyrrhenum (MC22) [30] and Margaritifer Sinus (MC19) [31]. In both cases the experience with the new technique was similar - auto-mapping produces a certain percentage of false detections. Careful visual inspection revealed that about ~20% of valleys (by length measure) are spurious detections ("false positives" in a computer jargon). However, even after manually removing the false positives, the resulting maps have several times more valleys (by length) than are present in the Carr map, affirming the viability of auto-mapping for updating the global map of VN. We have also applied our algorithm to map valleys in a large terrestrial site located in the Cascade Range, Oregon [28]. We have noticed a much smaller percentage of false positives, presumably because of the higher quality of the terrestrial DEM, and lack of U-shape topographic features other than valleys.

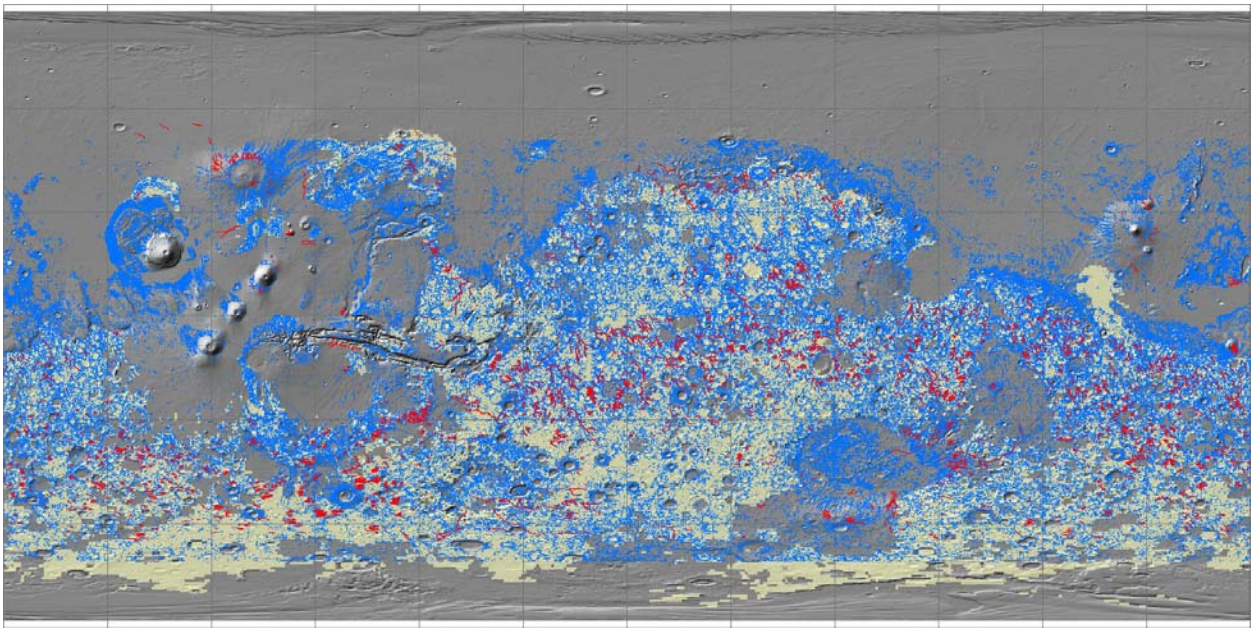

Figure 1: Map of valley networks on Mars. Blue lines indicate VN auto-mapped by the computer algorithm and red lines indicate VN mapped by Carr [15,16]. Yellow region indicates Noachian terrain.

Preliminary results of global mapping: Using the MEGDR as an input data we have auto-mapped VN located between 50˚ N and 70˚ S latitudes. The resultant map is in the form of an ArcGIS shapefile consisting of ~ 458,000 individual valley segments. Figure 1 shows (in blue) all the valley segments overlaid on a surface of the planet. For comparison, the VN mapped by Carr are shown in red. It is clear that auto-mapping produces a lot of false positives, especially outside of Noachian surfaces (Noachian surface is shown in yellow). It is also clear that within the Noachian the auto-mapping yields much more valleys than was mapped by Carr. It is difficult to judge the performance of auto-mapping by looking at the global map because the details are not visible. Figure 2 shows a close up centered on 13.77˚ W and 20.73˚ S. In this figure the background is the THEMIS daytime IR mosaic. Within the region depicted by Fig. 2 Carr has mapped a single large network of valleys. Note that this network is not correctly registered with the MDIM 2.1 standard. Our algorithm has mapped this network as well as several additional, less prominent networks. By looking at the background image we judge most (but not all) of these networks to be true VN. We submit that within the Noachian the quality of auto-mapping is similar to what is depicted on Fig.2 – most "newly mapped" valleys are real while few are false positives. Thus, within the Noachian, the uncorrected map may be used to derive maps of relative dissection density in order to address issues that do not require accurate values. However, false positives have to be eliminated for a "true" global map of VN.

One approach to the elimination of false positives is visual inspection. This is what we have done in a process of constructing maps of VN for MC19 and MC22 quadrangles. Although manual elimination of false positives left by auto-mapping is a much faster technique than an actual manual mapping, it is, nevertheless, desirable to develop an auto-elimination algorithm to complement the auto-mapping for a completely automated mapping solution. We are currently working to develop an auto-elimination algorithm based on a concept of machine learning. In machine learning known VN are used to "train" an algorithm about their properties. The results of training are used to build a mathematical model of a valley network against which all "candidate networks" are tested for either inclusion or elimination. Before machine learning technique is applied a database listing properties of all identified networks must be constructed.

Database for Martian VN: The shapefile produced by our mapping algorithm consists of segments that lack any numerical attributes describing their properties. The only purpose of this shapefile is to visually locate the segments on a map. In order to applied a machine learning technique for elimination of false positives additional attributes must be attached to each segment. To start this process we parse the set of 458,000 individual segments in order to determine which segments are associated with each other and thus could be combined into a "network." These candidate VN are then collected together and each is assigned an unique ID number. The output is a shapefile that is visually identical to the original input shapefile but contains only 184,000 objects – candidate VN.

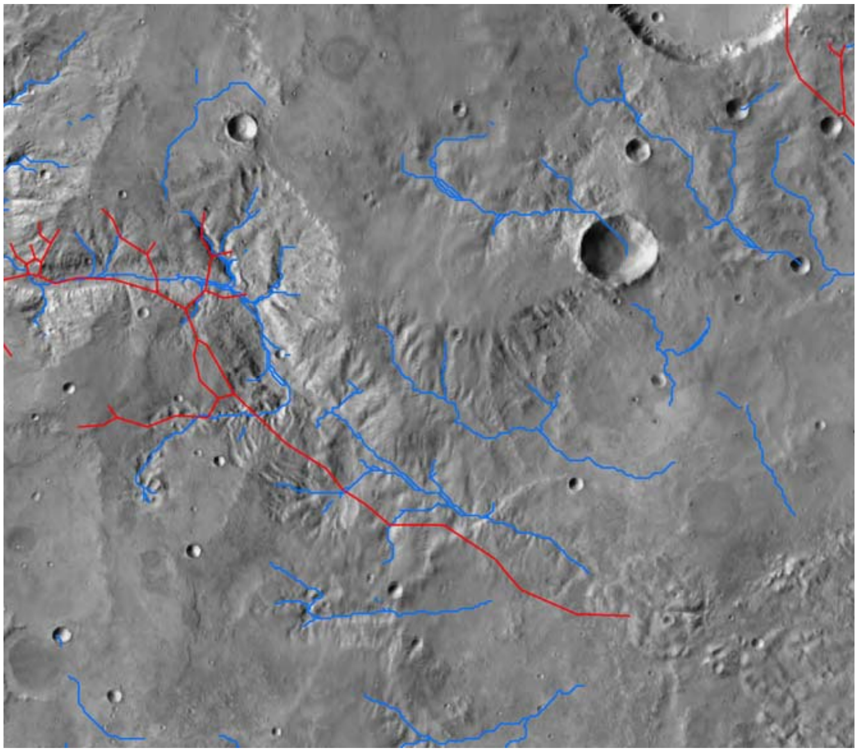

Figure 2: Close up of the valley networks map. Blue lines indicate VN automapped by the computer algorithm and red lines indicate VN mapped by Carr [15,16]. Background is the THEMIS daytime IR mosaic.

In the second step of building the database we identify a drainage basin (watershed) for each candidate VN. Each basin is further subdivided into constituent subbasins in order to determine the main stream for each network. Finally, in the third step, we assign numerical values of certain variables, such as elevation and geological unit underlying the VN candidate, to each object in the database.

The final result of these calculation is a database (an attribute table associated with the shapefile of VN candidates). This table contains numerical variables that would be used by a machine learning algorithm to distinguish between true VN and false positives. For each of the 184,000 VN candidates the database lists its ID number, coordinates of its outlet, its location (bounding box), a variable indicating whether the network has loops (about 2.3% of the VN candidates have loops and thus are non-dendritic; for such networks many attributes cannot be calculated), the underlying geological units, the number of segments in the network, network's order and magnitude [32,33,34], as well as the total length of all streams in the network. Further, the database lists the length of the main stream, the elevation of the outlet and source of the main stream, its sinuosity, slope and aspect. Finally, the database gives an area of drainage basin [32]. Figure 3 shows several VN described by our database. Each network is shown in red. Its outlet is indicated by a white dot, and its main stream is the longest stream from the outlet upstream. Associated drainage basin is shown in green.

Conclusion: Auto-mapping of VN (and other features) on Mars by means of computer algorithm is a feasible technique that offers speed and objectivity. A number of technical issues must be resolved before such technique could be applied routinely. The most pressing issue is how to eliminate false positive detection. Machine learning offers solution to this problem. A preliminary global map of VN has been created using the auto-mapping technique; it promises to be a significant update to the existing global map.

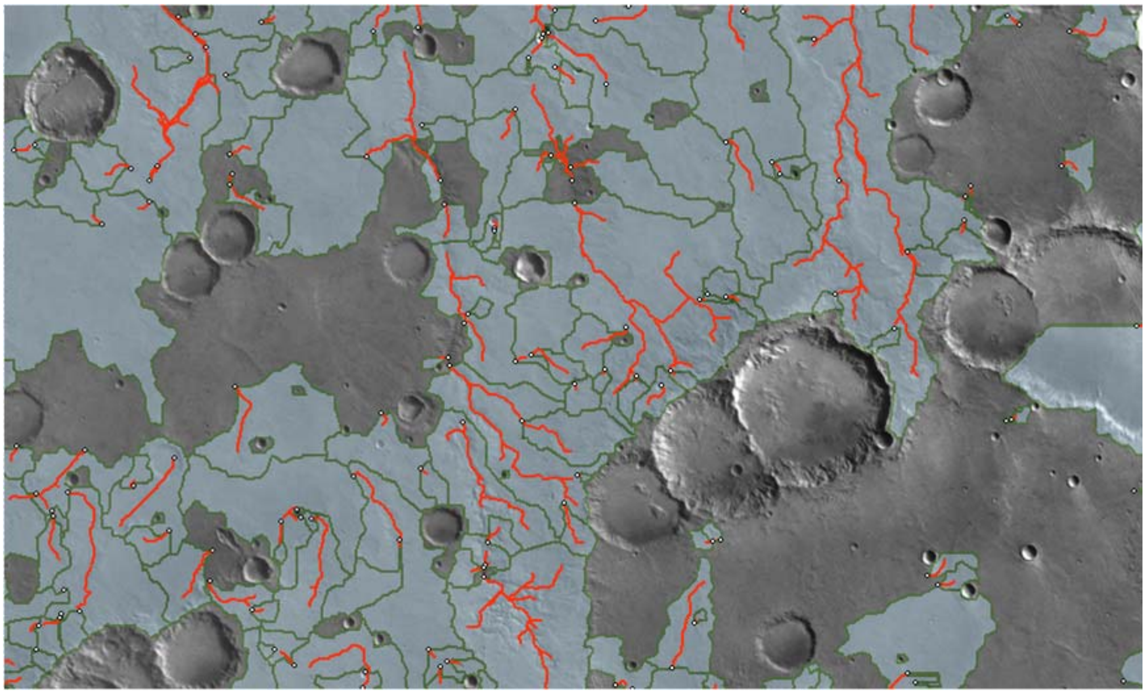

Figure 3: An example of database of valley networks. Each VN candidate is shown in red. Outlets of VN are indicated by white dots and green lines show boundaries of watersheds associate with each network. Regions that are not drained are transparent to the underlying Viking mosaic.

Acknowledgements. We acknowledge support by NASA (WL under grant WL under grant NNX08AM98G, TFS under grant NNG05GM316 and NNG06GE57G). A portion of this research was conducted at the Lunar and Planetary Institute under contract CAN-NCC5-679 with NASA. This is LPI Contribution No. 1440.

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