QUANTITATIVE ANALYSIS OF CONTROL NETWORKS IN PLANETARY IMAGERY. J. A. Mapel[1], L. A. Adoram-Kershner[1], J. R. Laura[1], and L. Weller[1], [1]USGS Astrogeology Science Center, 2255 N Gemini Drive, Flagstaff, AZ 86001.

Introduction: Orthoimages are a foundational data product within a planetary spatial data infrastructure and to accurately create them, correcting errors in the positions and orientations (ephemerides) is critical [1][2]. The photogrammetric control process corrects ephemeris errors by making repeated measurements of surface features across multiple images and then performing an adjustment [1][3]. The surface features are called control points and the measurements of them in individual images are called control measures. Collectively, all of the control points and control measures for a set of images is called a control network because it describes the photogrammetric relationships between the images [1]. Photogrammetric control has been used to correct planetary images for decades [4].

Early control networks were created by using recognizable features such as craters, as control points and manually measuring their locations in images [4][5]. These manually created control networks were highly accurate, but labor intensive to produce.

As sensor model software and image co-registration techniques improved, control network generation changed to use automatic bulk processing approaches. First, a regular pattern of control points is selected based on the image viewing geometries and/or the observed body. Next, all of the control points are back projected into the images that observed them to create control measures. All of the control measures for each control point are then co-registered (i.e., minor adjustments are made to shift the initial estimated image coordinate to as close to the actual coordinate as possible) so that they truly measured the same feature [6]. This approach has been used to successfully correct errors in images from many different sensors including Lunar Reconnaissance Orbiter (LROC) Narrow Angle Camera (NAC) [7], Mars Odyssey Thermal Emission Imaging System (THEMIS) [8], Mars Reconnaissance Orbiter (MRO) Context Camera (CTX) [9], and Apollo Metric Camera [10].

With recent advancements in computer vision, feature matching based techniques for generating control networks have gained popularity. All of these techniques use computer vision feature matching techniques to identify common features in pairs of images. Matching features become control measures that measure a control point generated by projecting the feature to a point on the observed surface. There is then a co-registration step to further refine the control measures and resultant control points. This additional step is required because most feature matching techniques are only accurate within a pixel and sub-pixel precision is desired [11][12]. This approach has been used to successfully correct errors in imagery from MRO CTX [13], MESSENGER Mercury Dual Imaging System (MDIS) [11], and OSIRIS-REx Camera Suite (OCAMS) [14].

These automated techniques allow for highly accurate error correction in large data sets, but they can also introduce errors that must currently be manually identified and corrected [7][8]. With control networks containing millions of control points and control measures, manual validation and correction is an extremely labor-intensive process. In terrestrial data sets, even larger volumes of data are fully controlled automatically using a variety of techniques [15]. While planetary data can be more challenging for feature matching methods, techniques for identifying errors and the overall quality of a control network should be adapted from terrestrial techniques [16]. We have identified a collection of outlier detection techniques and quality metrics from similar terrestrial applications that will apply to control networks generated from planetary data. We will present the results of this work at the conference. These results will inform the creation of future tools and techniques for controlling planetary imagery.

Test Networks: We have identified a number of control networks generated from planetary data that exhibit a range of issues which negatively impact the photogrammetric control process. The issues of interested are: (1) poor connectivity between overlapping images, (2) poor spatial distribution of control measures with in images, (3) measure co-registration errors, and (4) homogeneous viewing geometry for measurements of control points. We used a combination of control networks generated at the USGS Astrogeology science center to support other projects and manufactured networks with specific errors.

To investigate issues related to connectivity between images, we will use a control network of nine Galileo Solid State Imaging System (SSI) images of Europa. In this network all of the images are connected to each other via their connections to other images, but many overlapping images are not directly connected. We will also test a manually improved version of this network where all overlapping images are directly connected.

For all issues, excluding connectivity, we generated a small control network containing four MRO CTX images. Each control point was hand selected and measured to ensure there were no errors in the network. Then, we artificially introduced issues so that we can search for the presence of specific problems without noise. We chose MRO CTX as our image data set for two reasons. First, we are familiar with the data set and have ample experience generating control networks from it. Second, MRO CTX is a time dependent sensor and many issues we are interested in are more pronounced when controlling imagery from time dependent sensors.

To test poor control measure distribution we generated three control networks from our base MRO CTX network: one with all of the control measures removed from the middle of an image, one with all of the control measures removed from the end of an image, and one with most of the control measures clustered in a single region in an image.

In order to reproduce co-registration errors and feature miss-matches, we randomly selected control measures from our base MRO CTX network and shifted them by 5, 10, or 25 pixels in a random direction. We also, repeated this process with random noise added to all control measures in the network.

To test control networks with homogeneous viewing geometry, we created a control network from two orbits of MDIS NAC images where the maximum separation angle between the look vectors of control measures for each point were less than 5 degrees. We also created an improved network with images from additional orbits where the maximum separation angle of points with new measures was between 10 and 35 degrees.

We will also test each algorithm with control networks created at the USGS Astrogeology science center during the creation of scientific data products. These networks contain a mixture of issues, both known and unknown. First, we evaluate the Memnonia tile of the global THEMIS daytime IR network as a check with a large, relatively error-free network [8]. The network consists of 4398 daytime THEMIS IR images, 236,850 control points, and 1,304,457 control measures. Second, we will evaluate a large control network that was produced as part of a global MRO CTX mapping project [13].

Algorithms: We have identified three algorithms from the terrestrial photogrammetry and spatial analysis literatures. The algorithms quantitatively identify one or more of our issues of interest. It is highly unlikely that any single algorithm will detect all issues, so multiple algorithms may need to be used to identify all issues in a control network. The identified algorithms are: (1) data snooping, (2) redundancy, and (3) spatial coverage.

Data snooping is an outlier detection algorithm that is widely used in terrestrial photogrammetry [15]. A hypothesis test is performed for each control measure to determine if the control measure is an outlier based on the error in the network. Data snooping is a very powerful algorithm because it takes into account all of the factors that impact the adjustment of the control network [15].

Redundancy is a metric that measures the amount of shared information between control measures [17]. A good control point will have control measures with low variation in redundancy and a bad control point will have control measures with high variation in redundancy.

Lastly, we will investigate algorithms from spatial analysis to quantify control measure distribution within a single image. We have not identified a specific algorithm to apply, but there is a large volume of algorithms that are readily available in existing software packages that we can test.

Conclusion: We have collected a large set of control networks for planetary imagery that exhibit a broad range of issues and will apply a selection of algorithms from terrestrial remote sensing. We will present the results of our tests to quantify issues in control networks at the conference in an effort to improve how error in ephemerides for planetary imagery is corrected.

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