ASSESSING THE ROBUSTNESS OF FEATURE DETECTORS ON LUNAR IMAGES. E. J. Speyerer, Arizona State University, School of Earth and Space Exploration, PO Box 873603, Tempe AZ, 85287-3603 espeyere@asu.edu.

Introduction: The terrestrial remote sensing community adopted feature detection, description, and matching techniques from the machine vision community to identify and compare similar landforms and other distinctive attributes in vast image sets. Some applications of these tools include image registration, object localization, and 3D terrain reconstruction. With the recent addition of feature detection and matching routines in Integrated Software for Imagers and Spectrometers 3 (ISIS3) [1], a popular image processing tool for remotely sensed observations from planetary missions, feature-based matching is expanding to new worlds.

However, these new planetary bodies pose challenges for some feature detection, description, and matching routines that were originally derived for terrestrial applications. Countless non-unique and repetitive surface features (e.g. impact craters with similar appearance, boulder fields, etc.) cover many planetary bodies such as the Earth's Moon. This study provides insight into the effectiveness of various feature detectors on images acquired of the Moon with the Narrow Angle Cameras (NACs) onboard the Lunar Reconnaissance Orbiter [2] under various lighting and viewing geometries.

Feature Detectors: Feature registration and matching can be segmented into three parts: feature detection, feature description, and matching. In feature detection, a set of algorithms are applied to an image in order to identify "interesting" points or regions of an image. Among feature detectors, there are two general types investigated here: corner and blob. As the names suggest, corner detectors identify the corners or the intersections of two edges in an image and tags them as interest points. In terrestrial images, corner detectors are useful for tagging the corner of man-made structures, such as buildings and road intersections. blob detectors aim to detect unique regions in an image that have different properties than the remaining portion of the image, such as brightness. In this study, several common feature detectors were evaluated (Table 1).

Feature Detector	Feature Type	Scale Invariance
FAST [3,4]	Corner	No
Min. Eigenvalue Alg. [5]	Corner	No
Harris [6]	Corner	No
BRISK [7]	Corner	Yes
ORB [8]	Corner	No
SURF [9]	Blob	Yes
KAZE [10]	Blob	Yes

Table 1. Feature detectors used in this study.

Influence of Illumination on Feature Detectors: As stated, the goal of a feature detector is to identify interesting portions of an image such as the corners of objects or regions of the image that appear unique. Planetary missions capture images of the terrain under a variety of lighting and viewing conditions. Therefore, an effective feature detector must work on images acquired under a variety of solar incidence angles. As seen in Figure 1, we selected a 256 x 256 pixel region from three LROC NAC observations with a solar incidence angles of 15°, 45°, and 75°. The seven feature detectors were then applied to the cropped images and the 15 strongest detections from each al-

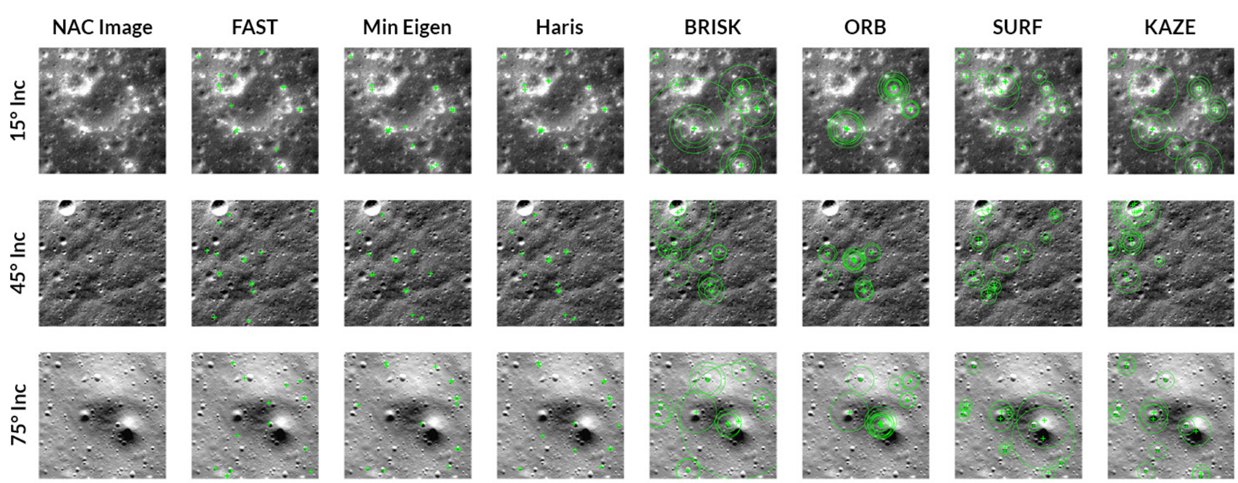

Figure 1. Application of seven feature detectors on three 256x256 pixel sub-images of LROC NAC observations with incidence angles of 15° (M109753063L), 45° (M139396321R), and 75° (M1285183949L).

gorithm were subsequently plotted.

At small incidence angles (15°), we see the corner detectors focus on the boundaries of albedo variations around small fresh craters. As the incidence angle increases to 75° the corner detectors start identifying the sharp shadow boundaries around small craters. When applying the ORB detector to the three cropped images, we see concentric circles around a small number of surface features. This indicates that the 15 strongest detection signatures are occurring over the same region and at slightly different scales. For the two blob detectors we investigated, we see that the center of the detections generally lie in the middle of regions with the same intensity values. In the case for the small incidence angle images (15°) the KAZE detector identifies the center of regions where the albedo is higher than the surrounding regolith while at larger incidence angles (75°), the feature detector is sensitive to the regions of the image in shadow.

Assessing the Robustness of Feature Detectors: A robust feature detector will identify the same point or region of interest regardless of rotation, scale, and noise. To examine the invariance due to rotation as a function of incidence angle, we selected a 1024 x 1024 region out of each NAC image. We then rotated the sub-image between 0 and 360° in 10° increments. To remove the impact of resampling and interpolation on the rotated images, we then reduced the image size of both the unmodified and the modified image by a factor of two making a 512 x 512 image.

We applied the feature detectors to the image before and after rotation and computed the ratio of common features detected in both images and the total number of features detected. Since the field of view is different in each image due to the rotation, we only counted detected features within 256 pixels of the image center. While the SURF descriptor is rotation invariant, the SURF detector struggled to detect the same surface feature when a slight rotation was applied to the image. Likewise, Minimum Eigenvalue Algorithm, BRISK, and Harris detectors did not perform as well when the image was rotated. On the other hand, the FAST, ORB, and KAZE detectors continued to match the same features when comparing to a rotated image.

Next, we assessed the feature detectors to changes in scale. In this case we resampled the LROC NAC sub-image from 1024 x 1024 to 512 x 512 and applied each feature detector to both images then compared them to identify how many features were detectible in the lower resolution image. As expected, the corner detectors that are scale independent fared better than the corner detectors that were not designed for detecting features over a range of scales. Ranked from best to worst in terms of repeatability at small incidence angles: BRISK (78%), ORB (58%), SURF (47%), KAZE (42%), Harris (20-40%), Min Eigen (25%) and FAST (15%). Overall, the repeatability was not affected by incidence angle with the exception of the Harris detector that was repeatable 40% of the time when the incidence angle was small (< 20°).

Finally, we assessed the performance of each detector to noise. Depending on the planetary mission and instrument, different types of noise patterns effect the image. For example, some instruments suffer from salt and pepper noise due to bit errors while the quality of other images are reduced by Gaussian noise. At small incidence angles, the performance of the FAST and BRISK detectors suffered greatly with the inclusion of salt and pepper noise (2.5% of pixels effected) resulting in 40 to 140 times as many detections as the original images without noise. This is likely due to corner detectors matching the smallest detectable features, which in this case is the salt and pepper noise pattern. However, at high incidence angles, the effect of the noise was reduced on both detectors. Meanwhile, the two blob detectors suffered the least from the additional image noise.

When examining the robustness to Gaussian noise with a mean of zero and a variance of 0.001, 0.011 and 0.021, we found that at small variance levels, the Harris corner detector suffered the worst and at higher levels the FAST detector was more susceptible to the Gaussian noise. Again, we see that the effect of the noise decreases as the incidence angle increases and the two blob detectors (SURF and KAZE) as well as the Minimum Eigenvalue Algorithm suffered the least from the inclusion of additional Gaussian noise.

Conclusions: Understanding the robustness of feature detectors is important when selecting an algorithm. These detections provide input into the feature description routines and ultimately in to matching algorithms. If a feature detector cannot reliably detect the same features with slight image alterations, then it will hinder the later feature matching processes. In general, the corner detectors focused on smallest features in the image and slight variations in surface reflectance, while the blob detectors identified regional trends in the dataset. As a result, the performance of corner detectors suffered more from changes in image scale and noise than either blob detector analyzed.

References: [1] Anderson et al. (2004) LPSC, #2039. [2] Robinson et al. (2010) *Space Sci. Rev.* [3] Rosten and Drummond (2005) IEEE Inter. Conf. on Comp. Vis. [4] Rosten and Drummond (2006) *European Conf. on Comp. Vis.* [5] Shi and Tomasi, 1994 *IEEE Conf. on Comp. Vis. and Pattern Recognition* [6] Harris (1988) Alvey Vision Conference [7] Leutengger (2011) Int. Conf. on Comp. Vision [8] Rublee et al. (2011) Int. Conf. on Comp. Vision [9] Bay et al. (2008) *European Conf. on Comp. Vis.* [10] Alcantarilla et al. (2012) *European Conf. on Comp. Vis.*