Developing Artificial Intelligence in Lunar Operations

Ronald H. Freeman, PhD

Chair, Space Operations &Support, Technical Committee, AIAA

Agenda

1. Background
2. Lunar Terrain Relative Navigation

   ---Crater Imaging and Detection
3. Lunar Crater Databases
4. Induction Algorithm: "The Black Box"

Backgound

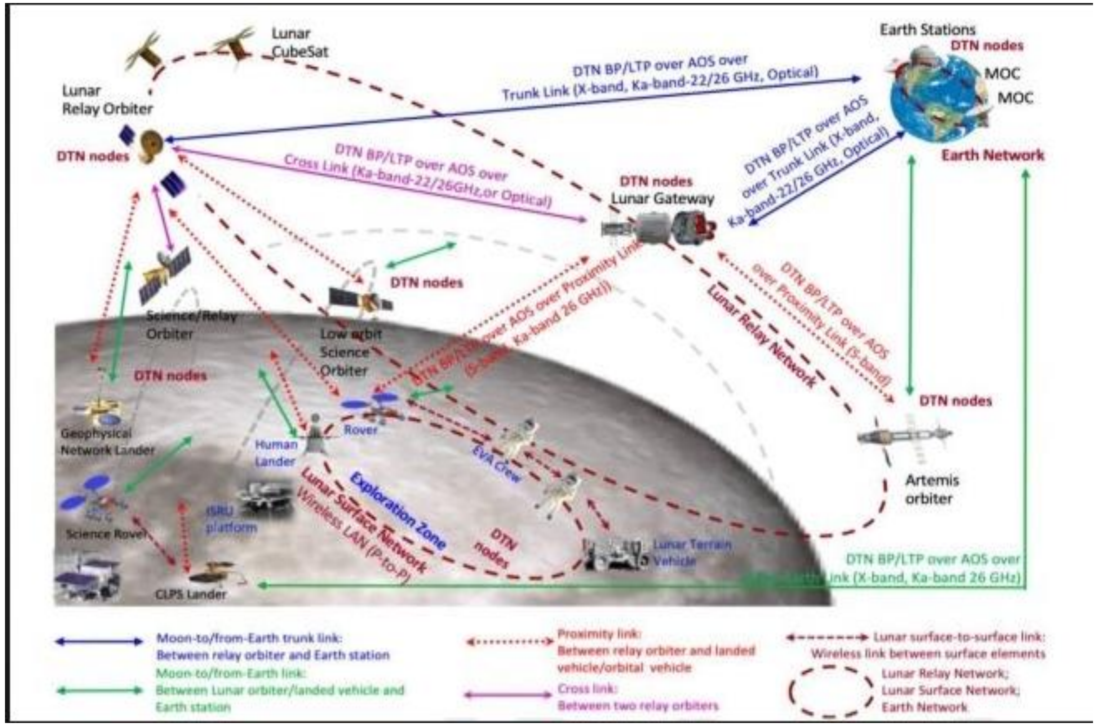
- The moon has many more craters than we thought, a new study finds. More than 109,000 new craters were discovered in the low- and mid-latitude regions of the moon using artificial intelligence (AI) that was fed data collected by Chinese lunar orbiters. The number of craters recorded on the moon's surface is now more than a dozen times larger than it was before. The findings were published Dec. 22 in the journal Nature Communications.
- Proposed missions to the Moon target the same small one by 5 km region on the rim of Shackleton crater, located at the South Pole of the Moon.The first landing on the lunar South Pole will`create a de facto operational zone that restricts future landings.
- On average, the horizon of the Moon is only around 1.5 miles from any given location (omitting hills, valleys, and craters). According to the international agreement, Artemis Accords, NASA and partner nations are required to provide public information regarding the location and general nature of their operations in order to inform the scale and scope of “Safety Zones” and prevent harmful interference. Moreover, Artemis Accords, Section 9, expresses a shared goal to preserve outer space heritage, including significant human or robotic landing sites, artifacts, spacecraft, in accordance with mutually developed standards and practices.
- Such constraints suggest an increasingly need to improve accuracy for lunar lander landings and rover navigation. The focus on accuracy leads to detecting craters and using them as landmarks because many of the crater locations have already been catalogued.
- The difference between the expected crater location (based on estimated spacecraft pose) and the matched crater location generates a measurement of the error in the pose estimate.

Crater databases overlaid on the Moon.

Craters from shown in blue and craters from shown in orange.

LunaNet to detect a large number craters in camera imagery

- Previous lunar landings relied mostly on inertial navigation methods, which time-integrate measurements from an inertial measurement unit (IMU). However, inertial navigation systems accumulate error over time and past lunar landing errors have been on the order of up to several kilometers. These errors pose a challenge because many of the locations of interest for future landing missions are in or near hazardous terrain, which motivates the need for increased landing precision.
- Current crater databases cover approximately 80% of the nearside of the Moon. LunaNet, visually detects craters in a camera image using a neural network and matches those detected craters to a database of known lunar craters with known latitudes and longitudes. The inclusion of these measurements in a landing navigation system can reduce estimation error and enable increased-precision navigation both in-orbit and during landing
- One method to reduce landing or navigation errors is terrain relative navigation (TRN) by a crater detector (LunaNet) consisting of a “front end” and a “back end”. The “front end” uses sensors to observe the terrain around a vehicle and match those observations to known terrain. The “back end” uses matches to generate a state estimate of the vehicle.
- [



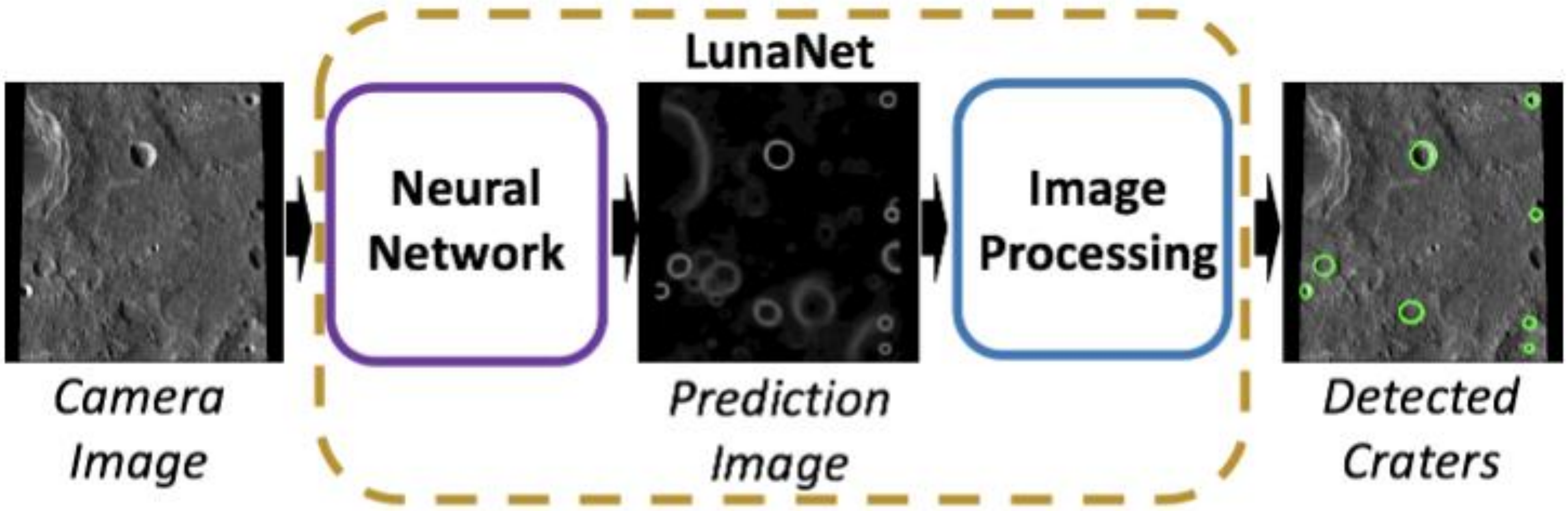
The data obtained from the active or passive sensor can be processed in two different ways for matching: **Correlation or Pattern Matching.**

- LunaNet, visually detects craters in a camera image using a neural network and matches those detected craters to a database of known lunar craters with known latitudes and longitudes.
- Matching involves finding a relationship between the sensor data that is acquired throughout a mission and the preexisting data about the area that is stored in a reference map.
- In correlation, the raw data from the sensor is correlated with map data (i.e. known latitudes and longitudes), and the area with highest correlation is accepted as a match. In pattern matching, features are extracted from the sensor data and treated as landmarks, which are then matched with landmarks from the map data
- It then utilizes the matches to generate measurements to be integrated into a navigation filter that estimates the spacecraft state (e.g. position, attitude, and velocity).

Since there exist datasets of known craters on the Moon, supervised learning can be utilized for a visual task.

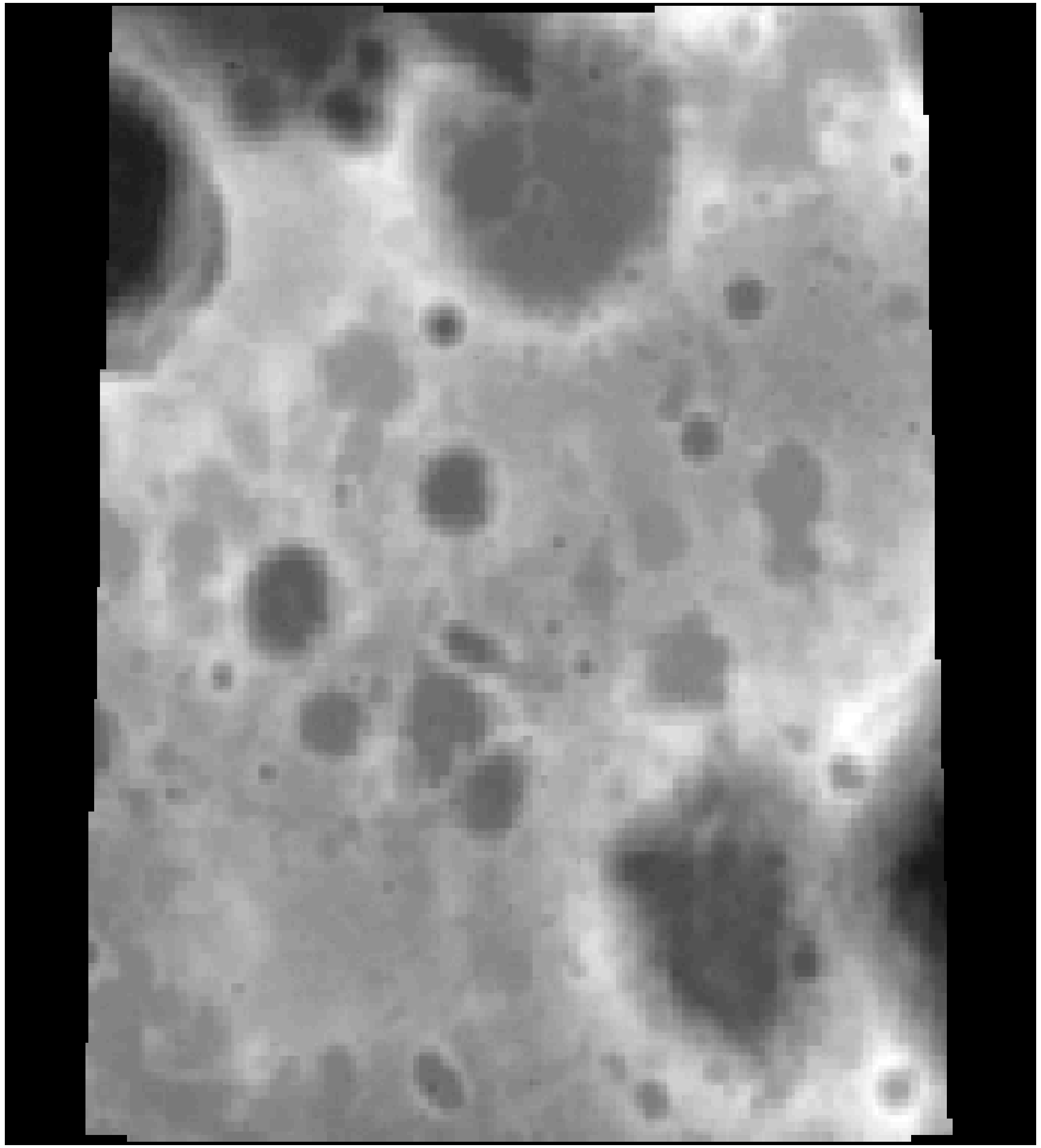
- Supervised learning is a type of machine learning that uses training data to determine a function that maps inputs to outputs. The training data in supervised learning consists of objects to be classified paired with labels of those objects.
- LunaNet, visually detects craters in a camera image using a convolutional neural network (CNN) and image processing methods.
- These crater detections are matched to a database of catalogued lunar craters with known latitudes and longitudes.
- The CNN subsystem outputs a prediction image, which is the CNN’s prediction of what pixels in the image are part of a crater rim. Brighter pixels correspond to higher certainty that that pixel is part of a crater rim.
- The prediction image is then input to LunaNet’s image processing subsystem. The image processing subsystem outputs a list of the locations and sizes in pixel space of the craters that were detected in the image. This list of crater detections is then output by LunaNet.

Trinary Edge Detector:To detect craters, it thresholds the input grayscale intensity image for bright patches and for dark patches, which correspond to crater rims and shadows. Edges of the patches are detected, and pairs of dark and bright edges are fitted with ellipses, which represent crater rims.

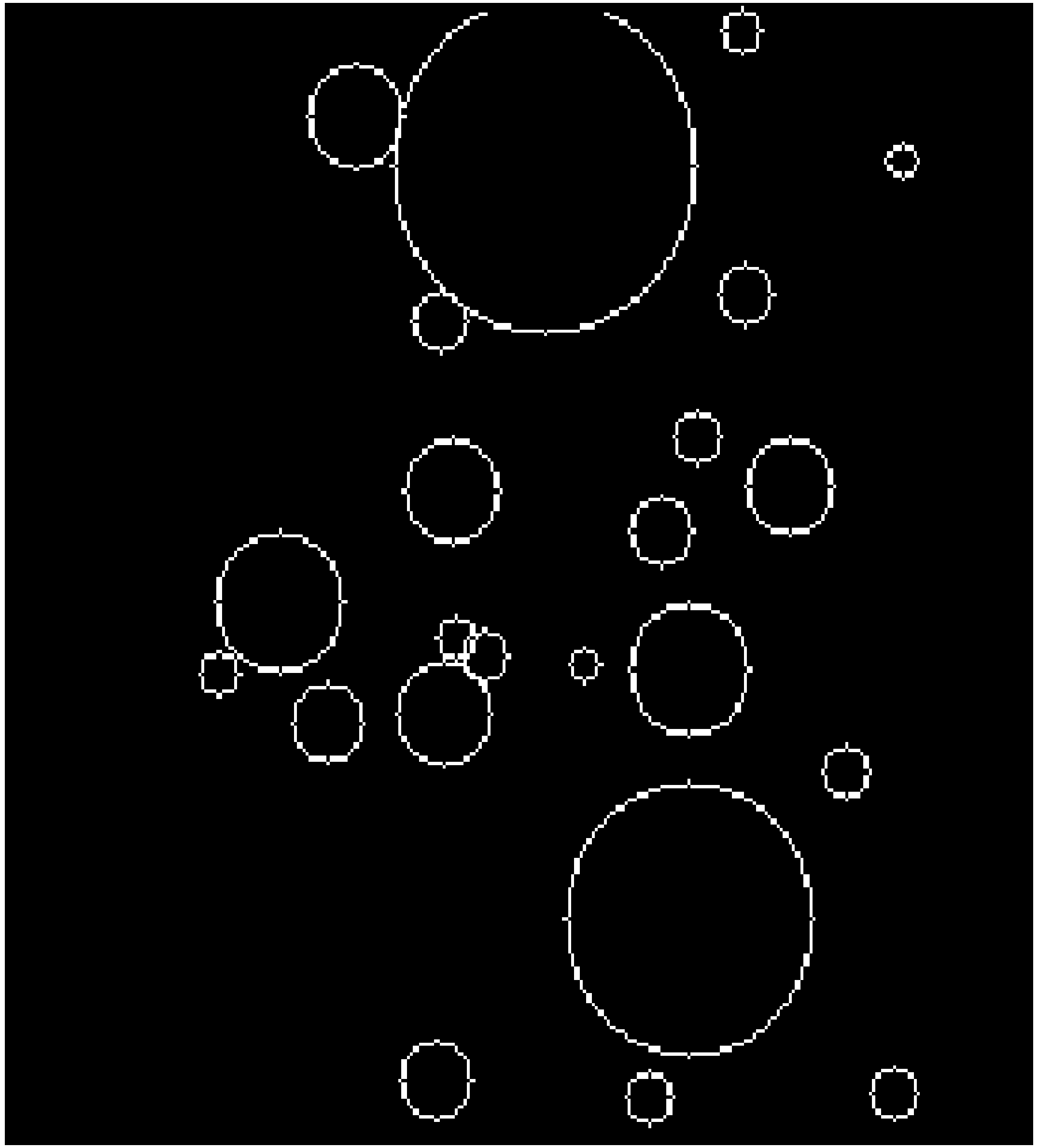


DeepMoon applies a CNN to detect craters from elevation data represented as overhead imagery (a pixel-wise classification of craters is performed)

- After generating a prediction image of crater rim locations, DeepMoon uses template matching to obtain discrete crater detections from the prediction image.
- DeepMoon utilizes elevation data in the form of digital elevation map (DEM) imagery, which has significantly different micro-scale variation than camera imagery and is not affected by lighting effects such as glare and shadowing.
- Obtaining an accurate elevation map in-flight requires a space-rated range sensor such as radar or LiDAR, which is more expensive on average than a space-rated camera. Due to this, LunaNet uses camera images and thus must accommodate for shadows and other forms of visual noise.



(a) Moon digital elevation map (DEM) input used to train DeepMoon.



(b) Ground-truth craters in camera field of view.

DeepMoon was trained using sets digital elevation maps (DEM) of areas on the Moon and their corresponding crater segmentation maps. The elevation images that DeepMoon was trained on are elevation maps of the Moon's surface obtained from the Lunar Reconnaissance Orbiter Camera (LROC) Wide Angle Camera (WAC), where a darker pixel corresponds to a depression and a lighter pixel corresponds to a raised area

- The training images that were input to train DeepMoon were sets of ground-truth classification data (known craters from a crater database) and digital elevation maps (DEM) of a corresponding area on the Moon.
- The elevation images that DeepMoon was trained on are elevation maps of the Moon's surface, where a darker pixel corresponded to a depression and a lighter pixel corresponded to a raised area.
- The ground-truth classification data were images with black backgrounds, and white rings corresponding to the pixel locations of crater rims.
- This ground-truth crater data was obtained from a combination of two human-generated lunar crater databases: from the 5-20 km database and from the >20 km database.
- DeepMoon was trained for four epochs on 30,000 DEM images

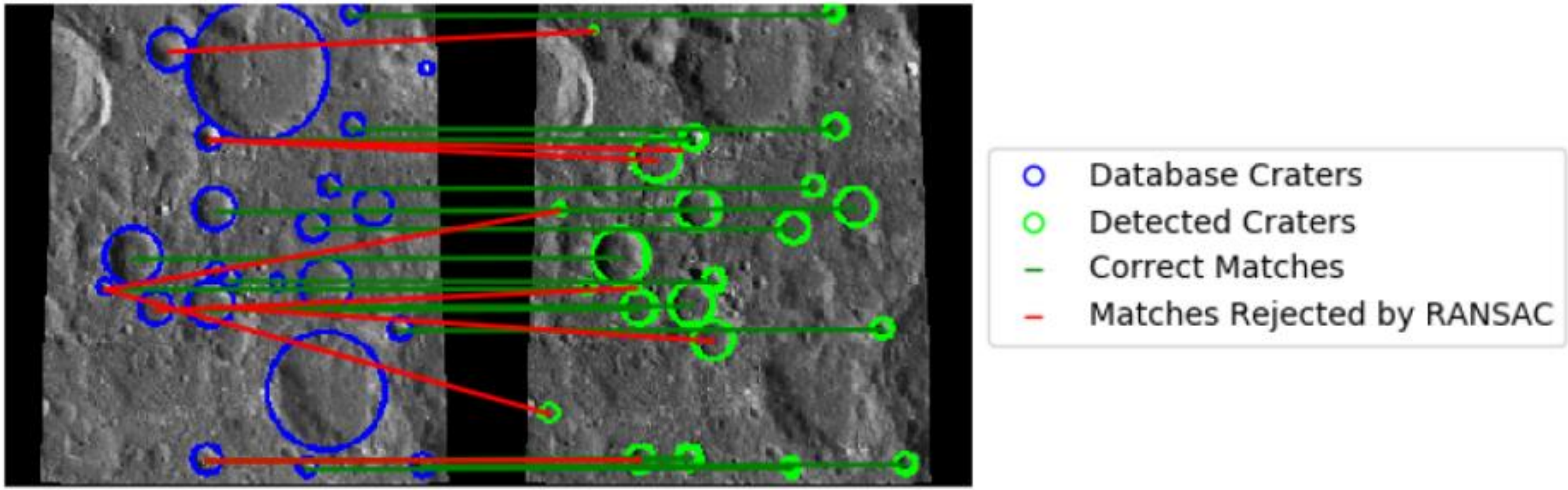
The search area contains all the known, catalogued craters for that area, with their latitudes, longitudes, and radii. Such known craters are projected into the camera pixel space, giving each known crater a size and location in pixels, based on the location estimate.

- LunaNet combines a CNN with image processing to detect craters in lunar surface imagery that is captured by an onboard camera in real-time.
- The output of the neural network is a grayscale image with brighter pixels corresponding to predicted crater rims. This output prediction is processed to identify likely craters in the image.
- These craters are matched against the databases of known craters from in order to identify their true locations on the surface of the Moon.
- The detected crater centers in the image and the known 3D locations of the craters can then be passed to a navigation filter to be used as measurements to improve the spacecraft’s position and attitude estimates and correct for drift from the inertial sensors.
- A spacecraft location estimate enables the prediction of what craters should be in the camera field of view.
- In order to test the crater matching performance, a search area is centered at the estimated spacecraft location and is as wide as the camera field of view.

Matching process of detected crater with database craters.

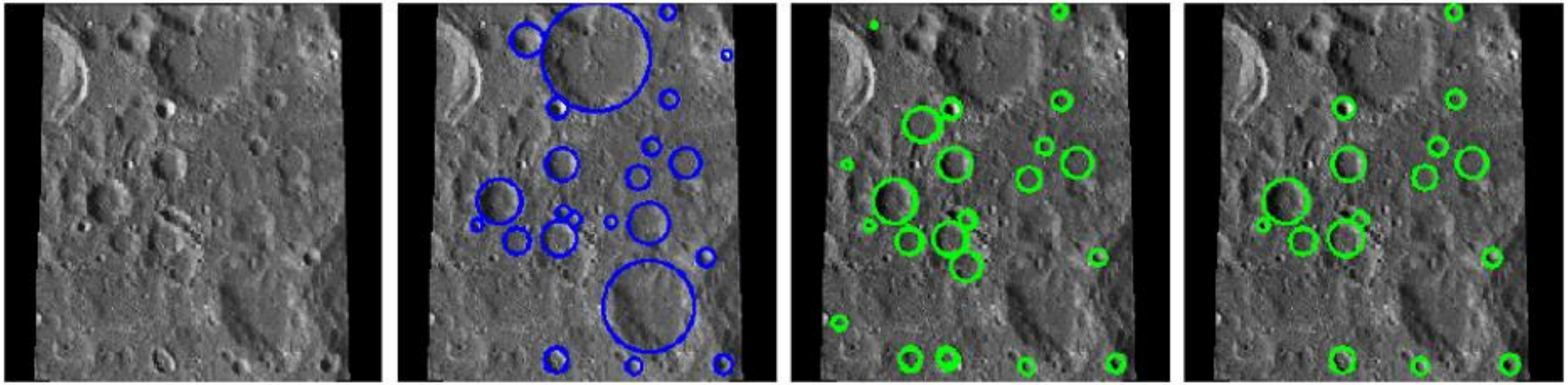
- The detected craters are matched to the known craters by means of nearest neighbor matching.
- Each detected crater is paired with a known crater that is closest to it in x, y pixel space, as well as in diameter in pixels.
- These pairs are then processed with random sample consensus (RANSAC) to eliminate outlier pairs. A pair is determined to be an outlier if the translation vector between the detected crater and the known crater is sufficiently different from the translation vector of all inlier pairs

Ground-truth set of craters that appear in the crater database for this test area in blue, craters detected by LunaNet in light green. Inlier pairs marked with dark green lines, outlier pairs marked with red lines.



The difference between the matched crater location and the detected crater location generates a measurement of the error in the position estimate. This measurement can be used to improve the spacecraft position estimate by incorporating it into the navigation system. As the spacecraft moves around the Moon, repeated crater detections and matches can correct for the drift that is typical in inertial navigation systems.

Craters that were detected by LunaNet and matched to known craters in a representative LRO image with no noise added.

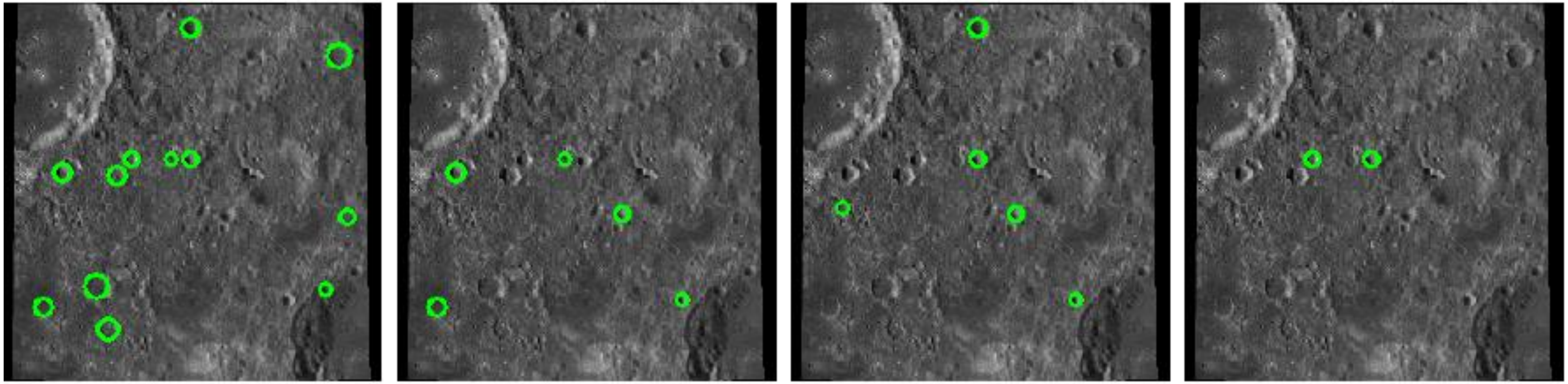


(a) Grayscale intensity image input to LunaNet. (b) Ground-truth craters in camera field of view. (c) Detected craters. (d) Matched craters.

Craters that were detected by different crater detectors and matched to known craters in a representative LRO image with no noise added.

- LunaNet produces at least twice as many good crater detections on average as DeepMoon, the neural network crater detector that it was based on, PyCDA, another neural network crater detector, and the trinary edge detector, a thresholding-based crater detector.
- Since a higher number of features corresponds to better navigation performance in terrain relative navigation, LunaNet appears to be a promising option for crater-based visual terrain relative navigation.

Crater detection performance of the four crater detectors on the same image, an LRO image of a region near the lunar equator. These images show craters that were detected and successfully matched to known lunar craters. The threshold levels of the trinary edge detector were tuned to optimally detect craters in this LRO imagery. DeepMoon, PyCDA and the trinary edge detector all detect less than 50% the number of craters that LunaNet detects.



(a) LunaNet (b) DeepMoon (c) PyCDA (d) Trinary edge

Induction Algorithm: The “Black Box”

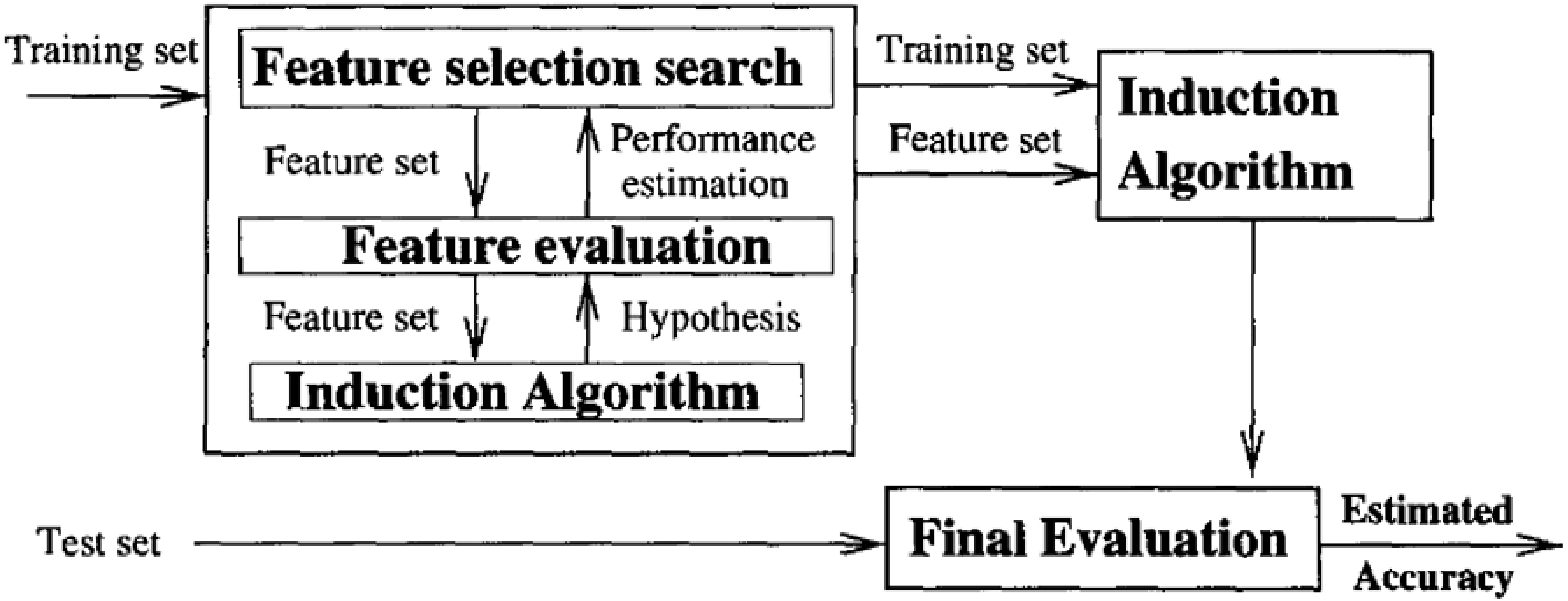
- In many computer science fields, such as pattern recognition, information retrieval, machine learning, data mining, and Web intelligence, one needs to prepare quality data by pre-processing the raw data. In practice, it has been generally found that data cleaning and preparation takes approximately 80% of the total data engineering effort **Knowledge discovery in databases (KDD)** (Zhang and Zhang 2002) as an iterative sequence of the following steps:
- **Data Pre-processing.** Data preparation comprises those techniques concerned with analyzing raw data so as to yield quality data, mainly including data collecting, data integration, data transformation, data cleaning, data reduction, and data discretization.
- **Data Mining.** Given the cleaned data, intelligent methods are applied in order to extract data patterns. Patterns of interest are searched for, including classification rules or trees, regression, clustering, sequence modeling.
- **Post Data Mining.** Post data mining consists of pattern evaluation, deploying the model, maintenance, and knowledge presentation.

Hyperparameters used to complete the additional intensity image training

Parameters used to create LunaNet by training [10] with intensity images

Parameter	Value
Learning Rate	10^{-4}
Batch Size	8
Filter Length	3
Weight Regularization	10^{-5}
Number of Filters	112
Dropout Fraction	0.15
Number of Runs	1

In the feature subset selection problem, a learning algorithm is faced with the problem of selecting a relevant subset of features upon which to focus its attention, while ignoring the rest. To achieve the best possible performance with a particular learning algorithm on a particular training set, a feature subset selection method should consider how the algorithm and the training set interact



The feature subset selection algorithm conducts a search for a good subset using the induction algorithm itself as part of the function evaluating feature subsets. The induction algorithm is run on the dataset, usually partitioned into internal training and holdout sets, with different sets of features removed from the data. The feature subset with the highest evaluation is chosen as the final set on which to run the induction algorithm.

Thank you.

ronaldhoracefreeman@gmail.com