Autonomous Geologist for Planetary Exploration

by

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Autonomous Geologist for Planetary Exploration

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Abstract

Proper mapping of a planet's surrounding can offer in depth understanding about the geology of the surface and environmental conditions. The high cost of planetary rover missions limits risk-taking and as a result restricts scientific exploration. This constraint is further compounded by limited autonomy that requires time-consuming intervention of Earth-based operators to ensure safe operation in previously unexplored areas.

The proposed autonomous classification system utilizes vision algorithms to gather textural information from the surface of rocks. The input is black and white images of hand samples taken in a controlled lighting environment. The classification is based on Haralick's textural feature extraction. Seven of the original 14 parameters introduced by Haralick (1973) are used: angular second moment, contrast, correlation, inverse difference moment, entropy, sum average, and sum of squares. Once the features are extracted, the system compares them against a catalogue of values from pre-processed rocks. Using Bayes' theorem, the system computes statistical probabilities of classifying the sample based on its former exposures.

The system has been tested using 180 sample points from 30 rock samples, and has achieved classification accuracy of 80%.

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List of Acronyms

Acronyms	Definition
2D	Two Dimension
APXS	Alpha Particle X-Ray Spectrometer
ASM	Angular Second Moment
AN1	Andesite 1
BA1	Basalt 1
BA2	Basalt 2
BA3	Basalt 3
CCD	Charge Coupled Device
CG1	Conglomerate 1
CG2	Conglomerate 2
CG3	Conglomerate 3
CheMin	Chemistry and Mineralogy
CK1	Chalk 1
CoC	Circle of Confusion
DB1	Diabase/dolerite 1
DL1	Dolostone 1
DoF	Degree of Freedom
DR1	Diorite 1
f-stop	Focal ratio
GB1	Gabbro 1

Acronyms	Definition
GLCM	Gray Level Co-occurrence Matrix
GLDM	Gray Level Difference Matrix
GLRLM	Gray Level Run Length Method
GN1	Gneiss 1
GN2	Gneiss 2
GR1	Granite 1
GR2	Granite 2
GS1	Greenschist 1
GY1	Gypsum 1
IDM	Inverse Difference Moment
ISO	International Standards Organizations
JPL	Jet Propulsion Laboratories
KM1	Komatiite
LIBS	Laser-Induced Breakdown Spectrometer
LM1	Limestone 1
LRV	Lunar Rover Vehicle
mini-TES	Thermal emission spectrometer
NASA	National Aeronautics and Space Administration
PR1	Periodotite 1
PR2	Periodotite 2
PSM	Power Spectral Method
PU1	Pumice 1

Acronyms	Definition
RH1	Rhyolite 1
RH2	Rhyolite 2
SD1	Sandstone 1
SD2	Sandstone 2
SH1	Shale1
SL1	Slate 1
US	Unite States
WL1	Wollastonite 1

List of Nomenclature

Nomenclature	Definition
$p(i,j)$	Count for element (i,j)
N_i	Number of rows in the GLCM
N_j	Number of columns in the GLCM
p_x	Horizontal pixel sums of GLCM
p_y	Vertical pixel sums of GLCM
p_{x+y}	Horizontal and vertical pixel sums of GLCM
μ_x	Horizontal mean of p_x
μ_y	Vertical mean of p_y
σ_x	Horizontal standard deviation of p_x
σ_y	Vertical standard deviation of p_y
ε	Epsilon
ξ	Mean
σ	Standard deviation

1 Chapter: Introductions

1.1 Context

Detailed mapping of a planet's surroundings from an exploration rover can reveal critical cues about the geology of the surface and past and present environmental conditions (Thompson et al., 2005a). Only nine rovers have successfully landed on other celestial bodies. Designed by the Soviets, Lunokhod 1 (1970) and 2 (1973) both traversed the lunar surface analyzing the mechanical properties of soil while transmitting close-up and panoramic images of their surroundings back to Earth. The Americans designed a Lunar Rover Vehicle (LRV) to assist the crew on their traverses on the surface of the moon during the Apollo 15 (1971), 16 (1972), and 17 (1972) missions. Moreover, four US-lead exploration rovers – Sojourner (1997), Spirit (2003), Opportunity (2003), and Curiosity (2012) – have identified a variety of geomorphological structures and geological material on the surface of Mars. The ever-growing list includes alluvial fans with dominantly gravel-size sediment (Moore and Howard, 2005), meteorites (Schröder et al., 2008), basalts with columnar jointing (Milazzo et al., 2009), carbonates (Morris et al., 2010), aeolian dunes exhibiting cross-bedding (Hayes et al., 2011), and conglomerates with centimetre-size rounded clasts (Williams et al., 2013).

The current high-cost of planetary rover missions, however, limits risk-taking. This constraint is further compounded by limited autonomy that requires time-consuming intervention of Earth-based operators to ensure safe operations in previously unexplored areas. The result is a frequently idle rover that misses potential scientifically valuable

targets due to a lack of a prior knowledge about its current local surroundings. To enhance productivity, there would be added benefit if geological investigation could be undertaken with minimal human assistance.

1.2 Objectives and Approach

This thesis reports on a promising approach to autonomous geoscience centered on the development of a rock classification system based on image processing using Bayesian networks. Whereas human geologists use an extensive suite of visual cues (e.g. colour of streak on a ceramic plate, relative proportion of grains of different sizes, etc.) and physical measurements (e.g. hardness comparisons, magnetism, etc.) to identify minerals and rocks, the proposed classification system relies solely on 2D black and white images. The system extracts textural parameters from these images and builds a catalogue of known rock samples. Then, using a Bayesian approach, the system assesses the data in the catalogue to evaluate the highest probability in classifying the unidentified rock sample. This is achieved based on the samples it has observed in the past. The objectives of this study were: (1) to extract textural features on images of rock samples, (2) to combine these parameters in a Bayesian image analysis system to achieve a robust classification, and (3) to validate the system on a wide variety of rock samples and assess its performance.

1.3 Background and Literature Review

Vision is the only modality sensor that can offer the most amount of information about an object and its surrounding environment (Ellery, 2013). Hence, it is the primary sensor

used by planetary exploration rovers for path planning and navigation purposes. Until now, interest in rover-based autonomous geology has been mainly in detection of obstacles and path planning (Halatci et al., 2008; Estlin et al., 2007; Maimone et al., 2006; Castano et al., 2006, 2004, 2003; Cheng et al., 2005; Thompson et al., 2005b). For instance, an application developed for mining industries, tries to identify large rocks (Cabello et al., 2002) to avoid costly machine blockage in mining. The system applies filters to the images in order to extract the shape and size of the surrounding rocks. Then, using neural network, it classifies the size and shape of the detected rocks with a reported accuracy of 70%. Another application that was designed with oil and gas industry in mind, uses computer vision algorithm to classify rocks (Goncalves & Leta, 2010). The approach extracts textural patterns using: Haralick's entropy parameter to assess the randomness of the patterns, Gray Level Co-occurrence Matrix to estimate the probability of reoccurring patterns (Haralick et al., 1973a), and Hurst coefficient, which is an approximation of fractal dimensions (Parker, 1997). Then, the system proceeds to classify the samples via a fixed (NFHB-CLASS model) and an adaptive (neural network) classifier. The results of their research indicate that the fixed classifier performs better, with a classification accuracy of 73%. Gneiss, basalt, diabase, and rhyolite were used for their studies. Hence why, I too included these rocks in my experiments.

Another study focused on the classification performance of planetary rovers on Mars and Mars-like environments based on colour, texture, and different resolutions (Halatci et al., 2007). The system applied filters to extract texture and colour of the images. Then, using a combination of Bayesian and meta-classifier techniques, it

proceeded to classify the obstacles (i.e. rough terrains, rocks, etc.) on the path of the rover. The paper concludes that due to mixed and sandy environments, texture-based classifiers have proven to perform better than colour based ones. However, due to sensitivity to resolution of the texture-based classifiers, the resolution was insufficient beyond 4 to 20 meters. Their system classified with an accuracy of 75%. Their additional study demonstrated that by increasing the resolution and variation of colours, the classifiers' performance was noticeably enhanced. Furthermore, other researchers have attempted to further the research in this field by training the system to distinguish between different types of obstacles, depending on the shape and colour of the object (Gallant et al., 2013; Fox et al., 2002; Hudson, 1992).

Moreover, today, the most advanced exploration rovers are capable of autonomous path planning and detecting obstacles. Researchers at the Jet Propulsion Laboratory (JPL) have been the leaders in this field by developing autonomous robotic products for planetary exploration missions. Based on JPL's publications, their vision algorithm approach only focuses on identifying the shape and size of the rocks (Gor et al., 2001; Castano et al., 2001). By applying filters, the sample's grayscale intensity variations were measured. Then, their results were compared with the mean of the set for a close match. Next, using contour detection, the physical shape of the rock was assessed in order to compare it with its inherent shape (Castano et al, 2003). The highly rounded rock indicates that the sample has gone under fluvial processing to be formed either by water, wind, or ice deposition. The shape can also tell us that the sediment may have travelled a significant distance during its transport. On the other hand, highly angular

shapes suggest that the rock has gone under minimal secondary processing and is close to its source.

Figure 1 and 2 illustrate their findings with an image of an igneous and a metamorphic rock. These two particular samples were used as they both possess the same mineral composition but have undergone different geological processes.

Figure 1: (Left) Original image of igneous and metamorphic rocks. (Right) Segmented image using grayscale intensity variation (Castano et al., 2003).

Figure 2: Contour detection (Castano et al., 2003)

Although planetary rovers are getting more sophisticated and are now instrumented with sensors such as mini-TES (thermal emission spectrometer), LIBS (laser-induced breakdown spectrometer), and infrared point spectrometers allowing them to make point measurements of specific mineral properties (Maki et al., 2012; Castano et al., 2007; Urmson et al., 2003; Wagner et al., 2001; Pedersen et al., 2001), their ability to use this information for autonomous decision making in real-time is still limited. For instance, the mission of the latest Mars rover, Curiosity, is to explore the possibility of past or present life on the red planet. It is also designed to determine whether Mars has ever had environmental conditions capable of supporting life. Its autonomous capabilities, developed in JPL, allow the rover to navigate and path plan to independently reach its target of interest. Using Chemistry and Mineralogy (CheMin) and Alpha Particle X-Ray Spectrometer (APXS) onboard the rover, Curiosity physically studies the samples to identify the elemental composition as well as the chemical and minerals found in the samples of rock and soil. However, the rover is unable to visually classify its samples. In my research, I have decided to use a much simpler approach. Using less instrumentation, I can classify the sample before proceeding to apply additional instruments to further analyze the samples.

Figure 3 illustrates one of the most exciting recent planetary exploration discoveries achieved by a rover: a conglomerate with centimeter-scale clasts. The rover has autonomous path planning and navigation capabilities to traverse to the rock of interest. However, the rover is incapable of classifying the rock sample by itself. Thus, Curiosity rover sent back images of the sample to the geologists at mission control (on Earth) for

analysis. As a result, the scientists studied the visible physical characteristics of the rock, and established a close resemblance to the similar conglomerates found in the Northwest Territories of Canada.

Figure 3: (Left) Conglomerate discovered by Curiosity on Mars. (Right) Conglomerate imaged in Hottah Lake, Northwest Territories, Canada (Williams et al., 2013).

Moreover, the geologists inferred that the presence of water based on the size and the shape of the clasts (the pebbles in the conglomerate) found within its matrix (the finer-grained rocks and minerals holding the larger clasts together). Although there was no water present at the site, the rock most likely has been exposed to water during the deposition of the sedimentary materials. The rounded shape of the clasts suggests that

they must have come into close contact with each other during the transportation process; which usually occurs in strong wind or water streams. However, due to the size and the weight of the clasts, it is unlikely that they could have been swept up and moved a significant distance via wind. The formation of this conglomerate most likely involved rapidly flowing fluid. This information is crucial, as it will help shape future planetary exploration missions. Scientists believe that the discovery of water on another planet could consequently lead to signs of life.

Another team involved in developing autonomous exploration rovers, is Professor Whittaker's group at Carnegie Mellon University. Nomad, the autonomous rover, is comprised of a laser range finder to detect obstacle and a high-resolution pan tilt camera to search for meteorites in the Antarctic (Apostolopoulos et al., 2000). Since meteorites are generally very dark in colour, the system is able to easily identify samples in a snow-covered ground based on the contrast. It first, evaluates the image's average spectral intensity. Then, based on the size of the object and using bayesian network, the application evaluates the probabilities of whether meteorite is present in the surroundings. The paper further elaborates that the system is not ideal for autonomous geological classification purposes, as it requires better techniques to the data more accurately and independently.

To follow up with the developers of Nomad's recommendations for a more robust rock classifier, I studied Haralick textural feature extraction (Haralick et al., 1973a). Robert Haralick had used 243 images of 128 x 128 micrographs of sandstones for his

study (Haralick et al., 1973b). Applying his techniques, he was able to extract pore grain geometry of the reservoir rocks. Then, he classified the samples using piecewise linear-discriminant function with an accuracy of 89%. Haralick textural extraction technique proved to be the most reliable approach for comparing rock samples autonomously. However, piecewise linear-discriminant function is complex and requires the knowledge of independent variables to be categorized. Given that rock's textural patterns are much more complex when a larger selection is available, alternative classification approaches would be preferred for my work.

From the early stages of my research, it was quickly realized that utilizing Gray Level Co-occurrence Matrix (GLCM) is crucial to a successful texture extraction-based classifier. It is a tool used by Haralick and many others for second-order textural extractions. Alternatives to GLCM consist of Fourier-based, Gray Level Difference Matrix (GLDM), Gray Level Run Length Method (GLRLM), and Power Spectral Method (PSM). However GLCM has proven to be a much more powerful and reliable technique than the rest (Connors & Harlow, 1980; Millard, 2003). Also, studies have shown that GLCM is the ideal approach when classifying textural information, as opposed to using Markov Random Field, fractal, or Gabor filters (Ohanian & Dubes, 1992). Since the focus of my research was to visually classify rock samples via textural information of rocks, GLCM was chosen in my dissertation calculations.

Additionally, the literature review led me to the realization that Haralick textural feature extraction is a robust technique to assist in classifying rocks. My thesis research is

the first to extract the textural information using the technique from a wide range of rock samples. Also in the past, Bayes' theorem has been used to distinguish meteorites from other samples. However, my research contributions will be the first to use this probabilistic approach to classify rocks using complex set of textural information rather than only relying on the spectral intensity data.

2 Chapter: Image Acquisition

2.1 Selecting Rock Samples

In this study, a total of 30 hand samples, representing the three types of rock (igneous, sedimentary, and metamorphic) and a variety of textures, were selected for analysis. Table 1 lists the samples and their characteristics. Some of the samples were chosen because they exhibit classic features, such as basalt with vesicles (BA1) or ropy pahoehoe (BA2), others because of similarities to rocks found on Mars, such as conglomerate (CG2) (Figure 3).

Table 1: List of rock samples studied

ID	Type	Rock name	Distinctive features
AN1	Igneous	Andesite	Vesicular texture Pahoehoe
BA1		Basalt	
BA2		Basalt	
BA3		Basalt	Coarse-grained
DB1		Diabase/dolerite	
DR1		Diorite	
GB1		Gabbro	Coarse-grained Fine-grained
GR1		Granite	
GR2		Granite	
KM1		Komatiite	Vesicular texture
PR1		Peridotite	
PR2		Peridotite	
PU1		Pumice	
RH1		Rhyolite	
RH2		Rhyolite	

ID	Type	Rock name	Distinctive features
CG1	Sedimentary	Conglomerate	
CG2		Conglomerate	
CG3		Conglomerate	
CK1		Chalk	
DL1		Dolostone	
LM1		Limestone	
SD1		Sandstone	
SD2		Sandstone	
SH1		Shale	
GN1	Metamorphic	Gneiss	Dissolution veins
GN2		Gneiss	
GS1		Greenschist	
GY1		Gypsum	
SL1		Slate	
WL1		Wollastonite	

Unlike the Earth, significant amount of the lunar rocks contain high concentrations of anorthite crystals, as well as iron and titanium minerals (Papike et al., 1998). Thus, it is likely to find diorite, gabbro, and basalt on the moon; all three igneous rocks which were catalogued by the rock classifier in this thesis research (USGS, 2014).

The dark areas of Mars also have shown signs of olivine, pyroxene, and plagioclase feldspar (Nimmo & Tanaka, 2005). These minerals are commonly found in basalts formed when lava rapidly cools (Webster et al., 2011). Hence, geophysical studies propose that a substantial amount of the red planet's surface contains basalt, and a trivial amount of andesite also (Wyatt & McSween, 2002). Additionally, in the Gusey crater of Mars, Spirit rover had detected carbonates near clay minerals. Since both minerals form in moist environments, the discovery suggests that billions years ago, Mars was much

warmer and moist. It is assumed that the carbonates had formed from the combination of water and carbon dioxide (from the atmosphere). Upon formation, the deposits of carbonates would have had settled over time and been buried. Since Earth has significant carbonate deposits in the form of limestone, it is also expected to find such rocks inside the crater of Mars (McSween et al., 2004). Most recently, on its path to Glenelg, Mars Science Laboratory rover (also known as the Curiosity rover) discovered a conglomerate that bares similar resemblance to a sample from Hottah lake, in Canada (Webster & Brown, 2012). Conglomerate, andesite, basalt, komatiite, and limestone are some of the rocks expected to be on the surface of Mars; hence, samples from these category were catalogued and utilized in my dissertation's studies.

2.2 Imaging Rock Samples

All images were acquired using the same setup (Figure 4), on the same day (Oct. 25, 2012), in order to eliminate variations (i.e. changes in lighting) that would require additional normalization steps. For additional information about the photography setup, see Appendix A.

Figure 4: The set-up for image acquisition

Imaging was done outdoors on a cloudy day to ensure a natural diffuse lighting, minimizing shadows and specular reflections. A digital camera mounted on a frame took overhead images of the samples at normal incidence, at a distance of 50 cm (Table 2). Two different surfaces of each rock sample were imaged, originally in colour. For calibration purposes, an 18% gray card was used prior to taking an image to ensure that the colour balance remained consistent.

Table 2: Image acquisition parameters

Camera model	Canon Power Shot SD780IS Digital ELPH
Charge Coupled Device (CCD)	12.1 Mega Pixel, 1/2.3-inch
Shutter speed	0.0333 seconds
Aperture	f/5.6
International Standards Organizations (ISO)	125
Circle of Confusion	0.030 mm
Flash	Off
Camera mode	Macro
Auto zoom	Off
Image resolution	4000 x 3000 pixels
Image type	Colour
Camera-target distance	50 cm

2.3 Building the Image Library

Colour images were converted to grayscale intensity based on a weighted sum of their red, green and blue components. The intensity varied linearly between 0 (black) and 255 (white), in incremental steps of 1. The grayscale images were stored as unsigned 8-bit integers.

Subsequently, three 256 x 256 pixels, non-overlapping subsets of each black and white image were selected for analysis. Since two images of each sample were taken, this leads to a library of 6 images per sample (Figure 5 and 6). Each image covers a 3.5 x 3.5 cm² area on the sample's surface.

Figure 5: Image library (one image of each rock sample is shown). Each image has a resolution of 256 x 256 pixels, and 256 gray levels.

Figure 6: Examples of 6 non-overlapping images for 2 rock samples: granite (GR2) (top row), gneiss (GN1) (bottom row).

3 Chapter: Textural Feature Extraction

3.1 Gray Level Co-occurrence Matrices

Simple metrics, such as the average intensity and the standard deviation of the intensity distribution, are sensitive to external factors or did not provide enough discrimination between the black and white images of the different rock samples. For example, in operational conditions, the average intensity will vary according to lighting conditions, which is undesirable. The standard deviation of the intensity distribution is unaffected by the spatial distribution of pixels with different intensities, and can be the same for vastly different samples, which is also problematic (González et al., 2003). This is illustrated in Figure 7 for granite and gneiss which both feature the same mineral assemblage (feldspar, mica, quartz). The minerals, however, are distributed differently in these two rocks: they are randomly distributed in granite, giving it its classic “salt and pepper” appearance; they are organized in light and dark compositional bands in gneiss. To avoid these problems, a more advanced feature extraction technique based on Haralick parameters (Haralick et al., 1973a) and widely used for classification of satellite images (Tsaneva, 2008; Walker et al., 1995; Haralick and Shanmugam, 1974) was utilized.

Using Robert Haralick’s feature extraction techniques (Haralick et al., 1973a), was ideal as it is applicable to a range of image resolutions. For his research, he used the approach to classify the textures ranging from micro, aerial, and satellite photographs. The images were then processed in grayscale intensity, which is appealing to be utilized

in my research. Grayscale intensity reduces the complexity of the classification, in the event that a mineral could be present in different colours.

By combining the Haralick technique to other multidisciplinary approaches, future rovers' autonomous analytical capabilities would be enhanced. For instance, inspired by the biology of the vestibulo-ocular reflex, a rover can be trained to track targets in its visual fields. Thus, as the exploration rover approaches its target, it can evaluate whether the target is interesting enough for further analysis or whether it should reroute to an alternative objective site. All of this can be achieved as the resolution of the approaching target improves with the reduction of distance between the target and the rover.

The capability of maintaining quality resolution illustrates the product's reliability and robustness. For instance, the system is applicable to use as the future rover is maneuvering to approach the target and needs to stay focused on a product while the vehicle overcomes rough terrains. The system can stay focused on the target and classify it efficiently, without having to reach the target.

Figure 7: Intensity distribution histograms for samples granite (left: GR2_13) and gneiss (right: GN1_11). The average and standard deviation of the intensity is 141.37 and 30.96 and for the granite, and 120.26 and 32.91 for the gneiss.

The first step in the Haralick feature extraction technique is the computation of the Gray Level Co-occurrence Matrix (GLCM) (Appendix B). The GLCM counts the number of times adjacent pixels have the same intensity. It is configured to perform four scans of an image: along the horizontal axis (0° angle), the diagonal axis (45° angle), the vertical axis (90° angle) and the cross-diagonal axis (135° angle). Counts of similar intensities cluster diagonally on the GLCM, whereas abrupt intensity variations plot further away from the diagonal line.

Figure 8 shows the GLCMs of the granite and gneiss samples studied in Figure 7. Since the grayscale used in this study has 256 levels, each of the 4 GLCMs associated with an image has a dimension of 256×256 elements. The top left and bottom right corners of the GLCMs count dark and light pixel pairs, respectively. The granite image GR2_13 has a GLCM with higher counts in a narrow band along the diagonal,

corresponding to a frequent occurrence of adjacent pixels of same intensity; these higher count values are skewed towards lighter pixels (Figure 8, top row). The gneiss image GN1_11 where light and dark bands are juxtaposed has a more evenly distributed GLCM featuring more cases of adjacent pixels with different intensities (Figure 8, bottom row). The distribution of zero (black) and non-zero values, and the count value (represented by a grey shade) in each element of the GLCMs provide a rich source of discriminatory information that will be exploited in the calculation of Haralick parameters.

Figure 8: GLCMs for images granite GR2_13 (top row) and gneiss GN1_11 (bottom row), and scan angles 0°, 45°, 90°, and 135°. For display, the elements of the GLCMs have been multiplied by four; black corresponds to zero and white to 65,536 (256 x 256; maximum count possible).

3.2 Haralick Parameters

Haralick (1973) originally defined 14 parameters that can be calculated from the GLCM. In this study, 7 parameters were used; chosen amongst the most widely used: angular second moment, contrast, correlation, inverse difference moment, entropy (Tsaneva, 2008; Chen et al., 1998; MacLeod et al., 1996; Carstensen, 1992).

The results of the 0° , 45° , 90° , 135° GLCMs were averaged together. The analysis was continued with averaged Haralick parameters, which are rotationally invariant (Appendix B). This approach to textural analysis therefore leads to robust results regardless of the camera-target geometry, a desirable feature for rover-based imaging.

Figure 9 to 15 show bar graphs for each averaged Haralick parameter for the complete image library. There is no one-to-one unique relationship between a given rock sample and a particular Haralick parameter value. The short bars indicate that, for a given parameter, the 6 images of the same sample gave very consistent results. Larger bars denote more variability. The parameters are described below.

Figure 9: Angular second moment

Parameter angular second moment (ASM) (Figure 9) increases when adjacent pixels have similar intensities. The mathematical definition of ASM is:

$$ASM = \sum_{j=1}^{N_j} \sum_{i=1}^{N_i} [p(i,j)]^2 \quad (1)$$

where i and j represent the coordinates of the elements of the GLCM matrix ($i=0, j=0$ top left corner; $i=0, j=256$ top right corner; $i=256, j=0$ bottom left corner; $i=256, j=256$ bottom right corner). Variable $p(i,j)$ is the count for element (i,j) . N_i and N_j are the numbers of rows and columns (256) in the GLCM, respectively.

Samples with homogenous intensity such as rocks that have an even pale or dark surface have high ASM. Conversely, rocks with abrupt intensity changes showed much lower ASM results. This is the case for the granite (GR2) (high ASM) and gneiss (GN1) (low ASM) discussed above.

Figure 10: Contrast

Parameter contrast (Figure 10) is also sensitive to abrupt intensity variations. The mathematical definition of contrast is:

$$\text{Contrast} = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} [(i-j)^2 p(i,j)] \quad (2)$$

The factor $(i-j)^2$ in Eq. 2 is larger the further away from the diagonal line. The non-zero elements of the GLCMs for gneiss sample GN1 form an ellipse along the diagonal, which has a lower eccentricity than that of granite sample GR2 (Figure 8). Sample GN1 therefore has a higher contrast than sample GR2.

Figure 11: Correlation

Parameter correlation (Figure 11) evaluates the likelihood of pixel pairs and discourages gradual intensity variations on the basis that they are more predictable than sharp variations. The mathematical definition of correlation is:

$$Correlation = \frac{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \{p(i,j) - \mu_x \mu_y\}}{\sigma_x \sigma_y} \quad (3)$$

where p_x and p_y represent the horizontal and vertical pixel sums of the GLCM:

$$p_x(i) = \sum_{j=1}^{N_j} p(i,j) \quad (4)$$

$$p_y(j) = \sum_{i=1}^{N_i} p(i,j) \quad (5)$$

and μ_x, μ_y, σ_x , and σ_y are the mean and standard deviation of p_x and p_y , respectively.

Continuing with the example of granite (GR2) and gneiss (GN1) samples, gneiss has more abrupt variations between white and black bands and therefore a high correlation, whereas granite has a lower correlation associated with gradual changes from light grey (feldspar) to darker grey (quartz) to black (mica).

Figure 12: Inverse difference moment

Parameter inverse difference moment (IDM) increases when there are blotches of similar intensity in the image (Figure 12). The mathematical definition of IDM is:

$$IDM = \sum_{i=1}^{Ni} \sum_{j=1}^{Nj} \frac{p(i,j)}{1+(i-j)^2} \quad (6)$$

The factor $(i-j)^2$ is in the denominator in Eq. 6. Parameter IDM has the opposite behaviour as parameter contrast where the same factor appeared in the numerator; it enhances gradual contrast changes and depresses irregular pattern changes. The granite (GR2) sample has a higher IDM than the gneiss (GN1) sample. This is the inverse of what was observed for parameter contrast, as expected.

Figure 13: Entropy

Parameter entropy (Figure 13) measures disorder in an image. The mathematical definition of entropy is:

$$\text{Entropy} = - \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \{p(i,j) \log (p(i,j) + \varepsilon)\} \quad (7)$$

where ε is an arbitrary small positive constant (2.2204E-16) to avoid a negatively infinite entropy in the event of $\log(0)$. Moreover, entropy is expressed as a negative value. More uniform samples plot to the left in Figure 13, whereas samples with sharper intensity contrasts between neighbouring pixels, plot to the right. The granite (GR2) which exhibit more gradual intensity variations (more predictable behaviour) plots to the left of the gneiss (GN1) which exhibit more abrupt intensity variations (more chaotic behaviour) on the entropy bar graph.

Figure 14: Sum Average

Parameter sum average (Figure 14) is a measure of homogeneity of the GLCM of an image. Repeated intensity patterns in images produce high counts in GLCMs, and therefore large value of the sum average. The mathematical definition of sum average is:

$$\text{Sum Average} = \sum_{i=2}^{2N_i} ip_{x+y}(i) \quad (8)$$

$$\text{where } p_{x+y}(k) = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p(i, j) \quad (9)$$

$$\text{and } k = i+j \quad (10)$$

Observing the GLCM of the two rocks in Figure 8, the shapes are almost the same. This observation further verifies the sum average results being very to each other.

Figure 15: Sum of Squares

Parameter sum of squares (Figure 15) is a measure of variance. It evaluates the homogeneity of the textural patterns of images. The mathematical definition of sum of squares is:

$$\text{Sum of Squares} = \sum_{i=1}^{Ni} \sum_{j=1}^{Nj} (i - \mu)^2 p(i, j) \quad (11)$$

$$\text{where } \mu = \frac{\sum_{i=1}^{Ni} \sum_{j=1}^{Nj} p(i, j)}{Ni * Nj} \quad (12)$$

The more gradual the changes, the higher the number of adjacent pixels of similar intensities, and the more spread out patterns in the GLCM and a higher sum of squares. The granite (GR2) has an overall higher sum of squares than the gneiss (GN1) sample, although the variability within each sample (Figure 6) is such that the two bars almost overlap in Figure 15.

In summary, samples exhibiting gradual intensity variations will have a higher ASM, IDM and sum of squares, and a lower contrast, correlation, entropy, and sum average. Note that this analysis was performed for small pixels with a side length of 0.14 mm (3.5 cm/256 pixel).

3.3 Member functions

The member functions are built using the averaged Haralick parameters presented in the bar graphs (Figure 9 to 15). This is accomplished when the Haralick parameter of the 180 sample points (30 rocks x 6 images) is first evaluated. Then, each Haralick parameter of the 6 images per rock sample is averaged together. In the end, each parameter (consisting of the 30 normalized sample points for the 30 rocks) is distributed into three member functions: low, medium, and high. There are a variety of member function shapes available: triangular, square, bell-shaped, pi-shaped, etc. A combination of one gaussian and multiple sigmoidal member functions were used for this research. This is because their shapes offer a closer natural match to translate the probabilities.

The medium member function is defined by a Gaussian function of the form:

$$e^{\frac{-(p(i,j)-\mu)^2}{2\sigma^2}} \quad (13)$$

where the mean (ξ), was 10.1E6, and the standard deviation (σ) is 27.8E5. Mean and standard deviation were calculated based on the maximum and minimum of the range of the 30 normalized sample points per parameter:

$$\xi = \frac{\sum_{i=1}^{N_i} x_i}{N_i} \quad (14)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N_i} (x_i - \xi)^2}{N_i}} \quad (15)$$

Gaussian function was defined as the medium member function. To avoid fixed boundaries, a left and a right sigmoidal function were used to define the low and high member functions, respectively:

$$\text{Left sigmoidal} = \frac{1}{1 + e^{-a(p(i,j) - \sqrt{(2\sigma^2 \log(2)) - \mu})}} e^{\frac{-(p(i,j) - \mu)^2}{2\sigma^2}} \quad (16)$$

$$\text{Right sigmoidal} = \frac{1}{1 + e^{-a(p(i,j) - \sqrt{(2\sigma^2 \log(2)) - \mu})}} e^{\frac{-(p(i,j) - \mu)^2}{2\sigma^2}} \quad (17)$$

with

$$a = \frac{\log\left(\frac{\frac{1}{0.98} - 1}{\frac{1}{1 - 0.98} - 1}\right)}{3\sigma} \quad (18)$$

Variable a controls the sharpness of the sigmoidal function's slope. The drop off percentage was fixed to 0.98 which corresponds to 3 standard deviations of the Gaussian function.

Figure 16 demonstrates the 3 member functions for the ASM parameter. Furthermore, as an example, granite (GR2) is assigned a value of about 0.88 in the low member function, of 0.12 in the medium member function, and 0 in the high member function; totalling to a sum of 1. Additionally, gneiss (GN1) is categorized with a value of about 0.98 in the low member function, 0.02 in the medium member function, and 0 in the high member function, which too adds up to a total sum of 1. The member function plots of all 7 parameters are included in Appendix D.

Figure 16: Member Function of ASM

The purpose of this binning system is to build a catalogue for each parameter, which will later be used to calculate probabilities. Appendix C lists the catalogue for each parameter.

Table 3 lists the highest member function for each sample and offers an overview of the observations used for differentiating among samples. Unfortunately, each row in Table 3 does not provide a series of attributes, which can distinguish each sample uniquely. For example, samples BA3 and PR1 are duplicates. The similarity confuses the system and results in misclassifications, as it will be shown further on.

Table 3: Highest member function of catalogued samples. The row colouring alternates from one pattern change to another. Duplicates (GN2 and GS1, BA3 and PR1, and PR2 and SL1) are paired together in the same shade. There are 24 unique combinations, and 3 groups of duplicates.

	ASM	Contrast	Correlation	Entropy	IDM	Sum Average	Sum of Squares
GR1	Low	Medium	Medium	Medium	Low	Medium	Medium
GR2	Low	Medium	Medium	Medium	Low	High	Medium
DB1	Low	High	Low	Medium	Low	Medium	Medium
GN1	Low	High	Medium	High	Low	Medium	Medium
DR1	Low	High	High	High	Low	Medium	Medium
GB1	Medium	Low	Low	Medium	Medium	Low	Low
PU1	Medium	Low	Low	Medium	Medium	Medium	Medium
SH1	Medium	Low	Low	High	Medium	Low	Low
CG1	Medium	Low	Medium	Medium	High	Medium	Medium
CG2	Medium	Low	Medium	Medium	Medium	Medium	Medium
RH1	Medium	Medium	Low	Low	Medium	High	Medium
AN1	Medium	Medium	Low	Medium	Low	Medium	Medium
BA2	Medium	Medium	Low	Medium	Medium	Low	Low
KM1	Medium	Medium	Low	Medium	Medium	Medium	Medium
CG3	Medium	Medium	Low	Medium	Low	Medium	Low
LM1	Medium	Medium	Low	Medium	Medium	Medium	Low
RH2	Medium	Medium	Medium	Medium	Low	High	High
CK1	Medium	Medium	Medium	Medium	Low	High	Medium
GN2	Medium	Medium	Medium	Medium	Medium	Medium	Medium
GS1	Medium	Medium	Medium	Medium	Medium	Medium	Medium

	ASM	Contrast	Correlation	Entropy	IDM	Sum Average	Sum of Squares
BA1	High	Low	Low	Low	Medium	Medium	Low
BA3	High	Low	Low	Low	Medium	Low	Low
PR1	High	Low	Low	Low	Medium	Low	Low
DL1	High	Low	Low	Low	Medium	High	Low
SD1	High	Low	Low	Low	High	High	High
PR2	High	Low	Low	Medium	Medium	Low	Low
SL1	High	Low	Low	Medium	Medium	Low	Low
WL1	High	Low	Medium	Low	Medium	High	High
GY1	High	Low	High	Medium	High	High	High
SD2	High	Medium	Low	Low	Low	Medium	Low

4 Chapter: Probabilistic Approach

4.1 Bayesian Image Analysis

In the 1700s, Reverend Thomas Bayes first discovered a probabilistic approach to help better understand how to extrapolate causes from effects. He passed away prior to publishing his findings. However, in the 18th century, thanks to the help of his old friend, Richard Price, Pierre-Simon Laplace was introduced to Bayes' work and managed to make it available to the research sector by publishing it (McGrayne, 2012).

Today, the probabilistic approach is known as Bayes' theorem. In this research, the theorem was used to classify rock samples visually. Using the Haralick textural extraction features, parameters were extracted from images and compared against the catalogued measurements of rocks. The Bayesian probabilistic theorem is expressed as follows:

$$P(c|x) = \frac{P(c) * P(x|c)}{P(x)} \quad (19)$$

$$\text{Posterior} = \frac{\text{prior} * \text{likelihood}}{\text{evidence}} \quad (20)$$

“Posterior” is the probability to classify a sample, taking into account the Haralick parameters extracted from its images. “Prior” is the probability of classifying a sample without taking into account any observations; in this case, there will be a $\frac{1}{30}$ chance that a sample will be correctly classified. The sum of all possible prior probabilities adds up to 1. “Likelihood” is a conditional probability that a sample belonging to certain class has the associated observed value found in the catalogue. “Evidence” evaluates the marginal

probability of measuring a Haralick parameter (i.e. medium ASM) for a certain sample (i.e. gneiss (GN1)) or in all other samples but that sample, summed together:

$$(gneiss = true | ASM = medium) = \frac{(gneiss=true) * (ASM=medium | gneiss=true)}{[(ASM=medium | gneiss=true)+(ASM=medium | gneiss=false)]} \quad (21)$$

where $(gneiss = true)$ is the probability of detecting gneiss as an input sample is true. In his work, Reverend Thomas Bayes suggested that in the event when he didn't know what to assign his prior value, he would set all possibilities as equal probability at the start of calculations. Thus, in my research, the prior is at maximum uncertainty of $\frac{1}{30}$. The value is chosen as such because all 30 catalogued rock samples have an equal chance of being classified. However in planetary exploration missions, based on the environmental settings, the prior would be adjusted to enhance the probability of detecting certain rocks and weaken the probability of others. For example, if the rover is exploring along a volcano, the prior will be assigned a higher probability value for detecting a volcanic rock (i.e. basalt) than a sedimentary one (i.e. dolostone). Moreover, in ideal conditions, evidence will sum to 1 but due to external factors (e.g. dust, poor lighting), the results generally only add up to a value close to 1.

The Haralick parameters of 6 sample images from the input sample are evaluated. Then, average for each parameter of these 6 sample images is achieved. Although this normalization step does not completely eliminate the error estimate, it improves the performance of the classification noticeably. Moreover, during the initial testing phase,

each of the 7 chosen parameters was separately evaluated to explore the performance of the classification.

Table 4 lists the Bayesian probabilities of classification for 30 known samples using parameter ASM only. Each row in the table lists the confidence of the system in matching the input (labeled on the far left column) with the ones it has been previously catalogued in its history (labeled on the top row). Results are very poor, as expected, since only a minimum amount of information has been used. For example, in the case of andesite (AN1) input, the system is more confident that it is a match with gabbro (GB1) than the actual rock. In 3 instances, the system correctly classified the samples; one of which was when it classified diorite (DR1) with a 57.22% confidence.

The results presented in **Table 4** show clearly that using a single parameter is not sufficient. Consequently in the final test, all seven Haralick parameters were combined, that is, their calculated probabilities from the member functions were multiplied together, to increase the performance of the classification system. The equation below is an example of how the incorporated all seven Haralick parameters would appear:

$$\text{Posterior} = \frac{\text{Prior} * \text{Likelihood}}{\text{Evidence}}$$

$$\text{Posterior} = (\text{gneiss} = \text{true} \mid [\text{ASM} = \text{medium} * \text{Contrast} = \text{high} * \text{Correlation} = \text{medium} * \text{Entropy} = \text{high} * \text{IDM} = \text{low} * \text{Sum Average} = \text{medium} * \text{Sum of Squares} = \text{medium}]) \quad (22)$$

$$\text{Prior} = (\text{gneiss} = \text{true}) \quad (23)$$

$$\text{Likelihood} = [\text{gneiss} = \text{true} * \text{ASM} = \text{medium} * \text{Contrast} = \text{high} * \text{Correlation} = \text{medium} * \text{Entropy} = \text{high} * \text{IDM} = \text{low} * \text{Sum Average} = \text{medium} * \text{Sum of Squares} = \text{medium}] \quad (24)$$

$$\begin{aligned} \text{Evidence} = & \text{Likelihood} + [\text{gneiss} = \text{false} * \text{ASM} = \text{medium} * \text{Contrast} = \text{high} * \text{Correlation} = \text{medium} * \\ \text{Entropy} = & \text{high} * \text{IDM} = \text{low} * \text{Sum Average} = \text{medium} * \text{Sum of Squares} = \text{medium}] \end{aligned} \quad (25)$$

Assessing Table 5's Bayesian outcomes, it is expected to see the input sample to contain the highest percentage of probability for detection. This instance occurs diagonally across the table's matrix from (1,B) to (30,AF). The shaded regions in the table represent the highest posterior per input sample. Additionally, the bold framed shaded cells represent the correctly classified samples. In some cases, the highest posterior is a correct match but has a probability far from 100%. For example, andesite (AN1) is correctly classified but the highest posterior is only 23.89%. However, relative to the other posteriors (i.e. BA1 with %0.00, BA2 with %0.02, and DB1 with %0.05), it is distinctively higher.

Table 4: Bayesian posterior probabilities (%) using only the ASM Parameter

	AN1	BA1	BA2	BA3	DB1	DR1	GB1	GR1	GR2	KM1	PR1	PR2	PU1	RH1	RH2	CK1	CG1	CG2	CG3	DL1	LM1	SD1	SD2	SH1	GN1	GN2	GS1	GY1	SL1	WL1
AN1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
BA1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
BA2	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
BA3	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
DB1	13.69	0.04	8.11	0.04	51.19	57.22	4.68	52.34	52.72	6.24	0.01	0.05	9.83	0.97	8.71	21.15	8.80	12.03	33.38	0.07	8.40	0.00	0.04	0.29	56.62	26.53	15.06	0.07	0.02	0.05
DR1	13.69	0.04	8.11	0.04	51.19	57.22	4.68	52.34	52.72	6.24	0.01	0.05	9.83	0.97	8.71	21.15	8.80	12.03	33.38	0.07	8.40	0.00	0.04	0.29	56.62	26.53	15.06	0.07	0.02	0.05
GB1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
GR1	13.69	0.04	8.11	0.04	51.19	57.22	4.68	52.34	52.72	6.24	0.01	0.05	9.83	0.97	8.71	21.15	8.80	12.03	33.38	0.07	8.40	0.00	0.04	0.29	56.62	26.53	15.06	0.07	0.02	0.05
GR2	13.69	0.04	8.11	0.04	51.19	57.22	4.68	52.34	52.72	6.24	0.01	0.05	9.83	0.97	8.71	21.15	8.80	12.03	33.38	0.07	8.40	0.00	0.04	0.29	56.62	26.53	15.06	0.07	0.02	0.05
KM1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
PR1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
PR2	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
PU1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
RH1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
RH2	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
CK1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
CG1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
CG2	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
CG3	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
DL1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
LM1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
SD1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
SD2	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
SH1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
GN1	13.69	0.04	8.11	0.04	51.19	57.22	4.68	52.34	52.72	6.24	0.01	0.05	9.83	0.97	8.71	21.15	8.80	12.03	33.38	0.07	8.40	0.00	0.04	0.29	56.62	26.53	15.06	0.07	0.02	0.05
GN2	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
GS1	2.99	0.73	3.26	0.64	0.61	0.04	3.36	0.49	0.45	3.33	0.26	0.83	3.18	2.82	3.23	2.59	3.23	3.07	1.91	0.97	3.25	0.04	0.69	1.96	0.07	2.29	2.91	1.00	0.35	0.80
GY1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
SL1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31
WL1	0.69	35.04	1.31	35.91	0.02	0.00	2.37	0.01	0.01	1.75	39.36	33.95	1.05	9.73	1.21	0.37	1.19	0.82	0.15	32.49	1.26	42.01	35.37	20.54	0.00	0.24	0.61	32.24	38.56	34.31

Table 5: Bayesian posterior probabilities using a combination of All 7 Parameters

	AN1	BA1	BA2	BA3	DB1	DR1	GB1	GR1	GR2	KM1	PR1	PR2	PU1	RH1	RH2	CK1	CG1	CG2	CG3	DL1	LM1	SD1	SD2	SH1	GN1	GN2	GS1	GY1	SL1	WL1
AN1	23.89	0.00	0.09	0.00	0.05	0.00	0.00	0.65	0.01	1.79	0.00	0.00	1.50	0.50	0.64	0.21	0.00	0.00	5.25	0.00	1.56	0.00	0.11	0.00	0.00	1.11	0.44	0.00	0.00	0.00
BA1	0.14	98.76	0.68	98.47	0.00	0.00	23.72	0.00	0.00	14.88	85.80	17.64	12.48	0.24	0.00	0.00	8.28	0.03	0.13	0.45	21.75	0.19	95.22	0.00	0.00	0.00	0.01	0.00	83.90	0.00
BA2	3.31	1.01	91.95	3.25	0.00	0.00	75.08	0.00	0.00	33.76	5.29	30.66	3.18	0.00	0.00	0.00	1.29	0.00	40.26	0.00	40.83	0.00	1.51	0.24	0.00	0.01	0.05	0.00	3.16	0.00
BA3	0.18	99.78	49.74	99.96	0.00	0.00	98.43	0.00	0.00	39.25	99.98	99.78	13.27	0.01	0.00	0.00	16.83	0.01	1.20	0.02	65.99	0.01	99.30	6.03	0.00	0.00	0.00	0.00	99.65	0.00
DB1	90.90	0.00	0.96	0.00	99.89	0.12	0.00	94.95	13.53	4.94	0.00	0.00	2.48	0.19	18.40	10.42	0.00	0.00	76.65	0.00	3.66	0.00	0.01	0.00	86.58	18.31	3.44	0.00	0.00	0.00
DR1	25.61	0.00	0.14	0.00	99.99	100.00	0.00	100.00	100.00	0.18	0.00	0.00	0.16	0.01	23.50	99.95	0.00	0.37	20.59	0.00	0.06	0.00	0.00	0.00	100.00	81.55	88.89	0.00	0.00	0.00
GB1	0.35	10.78	65.16	21.41	0.00	0.00	94.92	0.00	0.00	22.43	34.64	92.91	9.29	0.00	0.00	0.00	11.92	0.01	17.44	0.00	45.68	0.00	2.05	39.42	0.00	0.00	0.03	0.00	78.15	0.00
GR1	18.72	0.00	0.08	0.00	4.85	0.01	0.00	93.53	77.42	0.70	0.00	0.00	1.57	0.09	3.38	43.41	0.01	0.13	17.14	0.00	0.51	0.00	0.00	0.00	22.87	45.98	28.98	0.00	0.00	0.00
GR2	14.99	0.00	0.00	0.00	1.31	0.02	0.00	98.60	99.32	0.22	0.00	0.00	1.47	5.81	85.72	98.54	0.00	0.77	3.31	0.01	0.10	0.00	0.00	0.00	28.18	92.45	58.21	0.00	0.00	0.00
KM1	1.08	0.02	0.15	0.00	0.00	0.00	0.02	0.02	0.00	2.42	0.00	0.00	1.91	0.14	0.03	0.01	0.19	0.05	0.66	0.00	1.04	0.00	0.02	0.00	0.00	0.59	0.57	0.00	0.00	0.00
PR1	0.18	99.78	49.74	99.96	0.00	0.00	98.43	0.00	0.00	39.25	99.98	99.78	13.27	0.01	0.00	0.00	16.83	0.01	1.20	0.02	65.99	0.01	99.30	6.03	0.00	0.00	0.00	0.00	99.65	0.00
PR2	0.08	89.91	42.46	95.97	0.00	0.00	92.89	0.00	0.00	13.04	99.25	99.88	3.20	0.00	0.00	0.00	4.67	0.00	1.57	0.00	24.23	0.00	62.15	89.39	0.00	0.00	0.01	0.00	99.84	0.00
PU1	0.11	0.24	0.02	0.02	0.00	0.00	0.12	0.00	0.00	1.39	0.00	0.00	5.73	0.11	0.00	0.00	1.98	0.32	0.21	0.03	1.26	0.00	0.02	0.00	0.00	0.40	0.36	0.00	0.08	0.00
RH1	1.88	0.23	0.01	0.02	0.00	0.00	0.00	0.00	0.00	3.26	0.00	0.00	7.77	67.63	10.50	0.03	0.38	0.47	0.08	17.33	1.24	0.01	0.29	0.00	0.00	4.99	0.79	0.00	0.00	0.11
RH2	1.83	0.00	0.00	0.00	0.00	0.00	0.00	49.76	96.40	0.04	0.00	0.00	0.32	92.08	99.81	99.60	0.00	0.73	0.03	21.10	0.01	0.00	0.00	0.00	0.02	88.19	44.57	0.00	0.00	1.82
CK1	3.31	0.00	0.00	0.00	0.01	0.00	0.00	24.00	37.15	0.11	0.00	0.00	0.45	15.40	67.75	86.98	0.00	0.18	0.13	0.13	0.04	0.00	0.00	0.00	0.02	44.34	19.08	0.00	0.00	0.00
CG1	0.00	0.17	0.01	0.00	0.00	0.00	0.10	0.00	0.00	0.35	0.00	0.00	2.27	0.03	0.00	0.01	76.85	88.41	0.01	0.12	0.11	0.01	0.00	0.00	0.00	1.23	6.53	1.89	0.04	0.00
CG2	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.28	0.00	0.00	1.88	0.06	0.00	0.04	2.31	8.61	0.03	0.03	0.15	0.00	0.00	0.00	0.00	1.93	5.38	0.00	0.00	0.00
CG3	42.80	0.01	4.78	0.01	0.29	0.00	0.10	0.17	0.00	9.23	0.00	0.03	2.34	0.01	0.01	0.01	0.01	0.00	38.25	0.00	12.98	0.00	1.36	0.00	0.00	0.11	0.11	0.00	0.00	0.00
DL1	0.02	33.58	0.00	1.65	0.00	0.00	0.00	0.00	0.00	0.32	0.01	0.00	5.76	99.75	36.63	0.02	0.67	3.29	0.00	99.99	0.14	99.95	6.22	0.00	0.00	3.37	0.35	0.78	0.04	99.99
LM1	2.53	0.18	7.37	0.08	0.00	0.00	1.47	0.00	0.00	12.12	0.01	0.02	2.97	0.00	0.00	0.58	0.01	6.92	0.00	9.00	0.00	0.21	0.00	0.00	0.00	0.06	0.14	0.00	0.06	0.00
SD1	0.00	85.54	0.00	8.89	0.00	0.00	0.02	0.00	0.00	0.40	0.01	0.00	6.88	99.42	7.98	0.00	48.49	73.36	0.00	100.00	0.10	100.00	1.92	0.00	0.00	2.15	0.43	98.48	0.63	100.00
SD2	28.05	35.15	2.59	53.60	0.00	0.00	0.33	0.00	0.00	18.52	34.52	1.05	3.45	1.03	0.01	0.00	0.01	0.00	3.45	0.01	25.61	0.00	98.94	0.00	0.00	0.01	0.01	0.00	0.30	0.00
SH1	0.19	1.37	60.04	2.61	0.00	0.00	86.57	0.00	0.00	9.62	5.99	95.41	3.48	0.00	0.00	0.00	4.87	0.01	20.70	0.00	20.14	0.00	0.21	99.96	0.00	0.01	0.06	0.00	87.54	0.00
GN1	43.94	0.00	0.24	0.00	100.00	99.99	0.00	99.99	99.89	0.38	0.00	0.00	0.28	0.02	17.45	99.22	0.00	0.03	37.02	0.00	0.14	0.00	0.00	0.00	100.00	61.81	54.26	0.00	0.00	0.00
GN2	0.16	0.00	0.05	0.00	0.00	0.00	0.00	0.18	0.06	0.49	0.00	0.00	0.61	0.08	0.05	0.31	0.23	1.39	0.10	0.00	0.12	0.00	0.00	0.00	0.00	2.82	8.28	0.00	0.00	0.00
GS1	0.16	0.00	0.05	0.00	0.00	0.00	0.00	0.18	0.06	0.49	0.00	0.00	0.61	0.08	0.05	0.31	0.23	1.39	0.10	0.00	0.12	0.00	0.00	0.00	0.00	2.82	8.28	0.00	0.00	0.00
GY1	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	3.73	0.01	0.00	0.00	0.29	75.24	8.12	27.29	22.67	99.83	0.00	99.97	0.00	99.98	0.00	0.00	0.00	32.34	52.83	100.00	0.02	100.00
SL1	0.08	89.91	42.46	95.97	0.00	0.00	92.89	0.00	0.00	13.04	99.25	99.88	3.20	0.00	0.00	0.00	4.67	0.00	1.57	0.00	24.23	0.00	62.15	89.39	0.00	0.00	0.01	0.00	99.84	0.00
WL1	0.00	2.99	0.00	0.05	0.00	0.00	0.00	0.00	0.01	0.06	0.00	0.00	1.89	99.56	52.23	0.68	0.78	50.16	0.00	99.99	0.02	99.95	0.24	0.00	0.00	14.69	5.18	76.34	0.00	100.00

The classifier's robustness was further verified when 23 uncatalogued samples were input into the system. The same rocks that the system had difficulty in classifying (Table 5), were the ones that resulted in a misclassification when an uncatalogued image of the rock was introduced. Since all 23 samples (as illustrated in Table 6) performed similarly to their pre-processed samples, it suggests that the system is stable and is behaving as expected.

Moreover, most uncatalogued rocks were assigned the same member functions as their predecessors. This is illustrated in the case of basalt (BA3). Its catalogued sample (shown in Table 5) and uncatalogued sample (shown in Table 6) were both misclassified as peridotite (PR1). Thus, it indicates that in both cases, the system binned the basalt (BA3) similarly. However, it is clear that the system did not assign the same member functions for catalogued sample and uncatalogued sample of limestone (LM1). This is demonstrated when the system misclassifies the catalogued sample (Table 5) as a komatiite (KM1) but misclassifies the uncatalogued sample (Table 6) as basalt (BA1).

The shaded cells in the following matrix represent the misclassified samples (i.e. basalt (BA3)) as other catalogued samples (i.e. peridotite (PR1)). For example, basalt (BA3)'s posterior is not the highest to be detected as itself. Instead, the system classifies the basalt (BA3) as a peridotite (PR1) due to its slightly (by 0.02th %) higher posterior than basalt. The false detection is due to the aforementioned (Table 3) duplicity of their Haralick outcomes once binned. Since both samples contain similar results when binned and catalogued, it is impossible for the system to differentiate between the two. Later on, under future work section, recommendations are made for addressing this issue.

Table 6: Bayesian posterior probabilities for the uncatalogued samples using a combination of all 7 parameters

	AN1	BA1	BA2	BA3	DB1	DR1	GB1	GR1	GR2	KM1	PR1	PR2	PU1	RH1	RH2	CK1	CG1	CG2	CG3	DL1	LM1	SD1	SD2	SH1	GN1	GN2	GS1	GY1	SL1	WL1
AN1	23.89	0.00	0.09	0.00	0.05	0.00	0.00	0.65	0.01	1.79	0.00	0.00	1.50	0.50	0.64	0.21	0.00	0.00	5.25	0.00	1.56	0.00	0.11	0.00	0.00	1.11	0.44	0.00	0.00	0.00
BA1	0.14	98.76	0.68	98.47	0.00	0.00	23.72	0.00	0.00	14.88	85.80	17.64	12.48	0.24	0.00	0.00	8.28	0.03	0.13	0.45	21.75	0.19	95.22	0.00	0.00	0.00	0.01	0.00	83.90	0.00
BA2	3.31	1.01	91.95	3.25	0.00	0.00	75.08	0.00	0.00	33.76	5.29	30.66	3.18	0.00	0.00	0.00	1.29	0.00	40.26	0.00	40.83	0.00	1.51	0.24	0.00	0.01	0.05	0.00	3.16	0.00
BA3	0.18	99.78	49.74	99.96	0.00	0.00	98.43	0.00	0.00	39.25	99.98	99.78	13.27	0.01	0.00	0.00	16.83	0.01	1.20	0.02	65.99	0.01	99.30	6.03	0.00	0.00	0.00	0.00	99.65	0.00
DB1	95.97	0.00	34.29	0.00	99.98	0.04	0.05	83.08	0.48	22.45	0.00	0.00	3.84	0.00	0.26	0.40	0.01	0.00	97.35	0.00	26.40	0.00	0.07	0.00	85.06	2.10	0.85	0.00	0.00	0.00
DR1	25.61	0.00	0.14	0.00	99.99	100.00	0.00	100.00	100.00	0.18	0.00	0.00	0.16	0.01	23.50	99.95	0.00	0.37	20.59	0.00	0.06	0.00	0.00	0.00	100.00	81.55	88.89	0.00	0.00	0.00
GB1	0.35	10.78	65.16	21.41	0.00	0.00	94.92	0.00	0.00	22.43	34.64	92.91	9.29	0.00	0.00	0.00	11.92	0.01	17.44	0.00	45.68	0.00	2.05	39.42	0.00	0.00	0.03	0.00	78.15	0.00
GR1	18.72	0.00	0.08	0.00	4.85	0.01	0.00	93.53	77.42	0.70	0.00	0.00	1.57	0.09	3.38	43.41	0.01	0.13	17.14	0.00	0.51	0.00	0.00	0.00	22.87	45.98	28.98	0.00	0.00	0.00
GR2	14.99	0.00	0.00	0.00	1.31	0.02	0.00	98.60	99.32	0.22	0.00	0.00	1.47	5.81	85.72	98.54	0.00	0.77	3.31	0.01	0.10	0.00	0.00	0.00	28.18	92.45	58.21	0.00	0.00	0.00
KM1	1.08	0.02	0.15	0.00	0.00	0.00	0.02	0.02	0.00	2.42	0.00	0.00	1.91	0.14	0.03	0.01	0.19	0.05	0.66	0.00	1.04	0.00	0.02	0.00	0.00	0.59	0.57	0.00	0.00	0.00
PR1	0.18	99.78	49.74	99.96	0.00	0.00	98.43	0.00	0.00	39.25	99.98	99.78	13.27	0.01	0.00	0.00	16.83	0.01	1.20	0.02	65.99	0.01	99.30	6.03	0.00	0.00	0.00	0.00	99.65	0.00
PR2	0.08	89.91	42.46	95.97	0.00	0.00	92.89	0.00	0.00	13.04	99.25	99.88	3.20	0.00	0.00	0.00	4.67	0.00	1.57	0.00	24.23	0.00	62.15	89.39	0.00	0.00	0.01	0.00	99.84	0.00
PU1	0.26	10.86	0.03	2.12	0.00	0.00	0.56	0.00	0.00	5.71	0.01	0.00	21.99	2.55	0.00	0.00	7.68	0.54	0.16	0.71	7.18	0.01	2.03	0.00	0.00	0.25	0.15	0.00	0.03	0.00
RH1	1.88	0.23	0.01	0.02	0.00	0.00	0.00	0.00	0.00	3.26	0.00	0.00	7.77	67.63	10.50	0.03	0.38	0.47	0.08	17.33	1.24	0.01	0.29	0.00	0.00	4.99	0.79	0.00	0.00	0.11
RH2	1.83	0.00	0.00	0.00	0.00	0.00	0.00	49.76	96.40	0.04	0.00	0.00	0.32	92.08	99.81	99.60	0.00	0.73	0.03	21.10	0.01	0.00	0.00	0.00	0.02	88.19	44.57	0.00	0.00	1.82
CK1	4.28	0.00	0.03	0.00	0.03	0.00	0.00	6.10	1.38	0.36	0.00	0.00	0.48	0.28	1.21	7.06	0.00	0.03	0.80	0.00	0.19	0.00	0.00	0.00	0.02	5.24	6.46	0.00	0.00	0.00
CG1	0.11	0.24	0.02	0.02	0.00	0.00	0.12	0.00	0.00	1.39	0.00	0.00	5.73	0.11	0.00	0.00	1.98	0.32	0.21	0.03	1.26	0.00	0.02	0.00	0.00	0.40	0.36	0.00	0.08	0.00
CG2	0.00	0.17	0.01	0.00	0.00	0.00	0.10	0.00	0.00	0.35	0.00	0.00	2.27	0.03	0.00	0.01	76.85	88.41	0.01	0.12	0.11	0.01	0.00	0.00	0.00	1.23	6.53	1.89	0.04	0.00
CG3	42.80	0.01	4.78	0.01	0.29	0.00	0.10	0.17	0.00	9.23	0.00	0.03	2.34	0.01	0.01	0.01	0.01	0.00	38.25	0.00	12.98	0.00	1.36	0.00	0.00	0.11	0.11	0.00	0.00	0.00
DL1	0.02	33.58	0.00	1.65	0.00	0.00	0.00	0.00	0.00	0.32	0.01	0.00	5.76	99.75	36.63	0.02	0.67	3.29	0.00	99.99	0.14	99.95	6.22	0.00	0.00	3.37	0.35	0.78	0.04	99.99
LM1	0.61	52.02	1.72	42.44	0.00	0.00	30.75	0.00	0.00	25.20	2.37	0.35	30.67	0.06	0.00	0.00	19.96	0.11	1.75	0.01	42.23	0.00	20.25	0.00	0.00	0.02	0.04	0.00	2.82	0.00
SD1	0.00	85.54	0.00	8.89	0.00	0.00	0.02	0.00	0.00	0.40	0.01	0.00	6.88	99.42	7.98	0.00	48.49	73.36	0.00	100.00	0.10	100.00	1.92	0.00	0.00	2.15	0.43	98.48	0.63	100.00
SD2	1.34	87.04	4.04	88.82	0.00	0.00	4.78	0.00	0.00	23.55	38.91	0.72	4.37	0.29	0.00	0.00	0.86	0.00	0.43	0.05	18.57	0.00	93.58	0.00	0.00	0.00	0.01	0.00	4.54	0.00

5 Chapter: Discussion

5.1 Classification Accuracy

The table below displays the impact -in terms of classification accuracy- of combining parameters when computing Bayesian posterior probabilities. To calculate the classification accuracy, the total of all correctly classified samples was added and divided by the sum of all rock samples that the system had evaluated. For example, in the case of combining ASM and contrast parameters to evaluate the posterior of 30 rock samples, only 6 rocks were correctly classified. Hence, the classification accuracy was $\frac{6}{30}$ or equivalently 20%.

Table 7: Classification accuracy increasing with the addition of Haralick parameters

ASM	x	x	x	x	x	x	x
Contrast		x	x	x	x	x	x
Correlation			x	x	x	x	x
Entropy				x	x	x	x
IDM					x	x	x
Sum Average						x	x
Sum of Squares							x
Classification accuracy (%)	10.00	20.00	40.00	50.00	56.67	76.67	80.00

Moreover, the addition of the remaining 7 Haralick parameters (sum variance, sum entropy, difference variance, difference entropy, information measures of correlation 1&2, maximal correlation coefficient) to improve classification accuracy was disregarded after examination of these results. This is because the rate of improving the classification accuracy significantly decreases (as shown in Figure 17) after the 6th parameter. Given

the relatively steady improvement of classification accuracy with the addition of each of the 7 parameters, it is not feasible to combine further more Haralick parameters. This is because the trade off of having the additional parameters to enhance the accuracy of classification was outweighed by its computationally expensive programming and processing. The purpose of autonomous robotics is to automate the system; so that communication delays resulting in mission inefficiencies are reduced. As a result, 7 of the Haralick parameters were out-selected as they were posed computationally complex calculations that demanded a significant delay in proceeding with the mission, while the system processed the classification results. Furthermore, since the Mars rovers have limited onboard resources (both power and computational capabilities), using all 14 Haralick parameters would have been an unproductive approach to alleviate the delays.

An example of the compromise (between enhancing the classification accuracy and the extra delay endured as a result of additional parameters), is as follows: the total processing time to extract 5 Haralick parameters (ASM, Contrast, Correlation, Entropy, IDM) from an image, was about 2 minutes. However, the addition of the last 2 parameters (Sum Average and Sum of Squares), significantly extended the total processing time by approximately an additional 40 minutes. The remaining other 7 Haralick parameters demanded far more computational processing time (of about an additional 2.5 hours) to calculate. Additionally, it is important to note that Robert Haralick reported that when he used the 14 parameters to classify micrograph images, he was able to achieve an 89% accuracy of detection (Haralick et al., 1973a). Since we have reached an accuracy of about 80% with half of his parameters, the comparison of the

results' performance along with the added delay of additional parameters, was the reason for stopping the extraction at the 7th Haralick parameter. It is worth mentioning that Information Measure of Correlation 1 & 2 were evaluated but the system crashed after 2.5 hours of attempting to run the algorithm. After the 6th attempt, the algorithm for both of those parameters was disregarded.

Figure 17: Classification accuracy vs. number of Haralick parameters used

In the event that the input sample is from a rock family that has not been catalogued before, the system will proceed to best classify the rock to its closest catalogued match.

5.2 Future Work

In the future, it would be ideal to shrink the bars in the bar graphs. That way, variability of the data is reduced and it is easier for the classifier to differentiate between the samples. Selecting parameters that produce bar graphs with condensed bars for each rock can reduce variation. For example, the Haralick parameter, inverse difference moment has the sample points for every rock spread out. This results in significant variation of results for each rock. In this case, replacing inverse difference moment with an alternative parameter that produces more condensed bars is desirable. Additionally, applying a normalization step would also stabilize the results and further reduce the variability of the results. Normalization is achieved by taking a set of sample images of a rock, then extracting the desired parameters from it, and averaging those results for each rock. The process is beneficial in diminishing the environmental impacts (i.e. lighting) and rock imperfections that contribute to the great variation of the sample points (Elteto and Toon, 2010).

The following figure is an illustration of swapping one of the 7 Haralick parameters with a more desirable one that offers smaller bar graphs:

Figure 18: An illustration of an Ideal Parameter

Moreover, exploiting images of samples that encompass larger surface areas would reduce the sensitivity of the textural features and reduce the variation seen in the bar graphs. This is concluded based on Haralick's personal application of the algorithm to classify micrograph photos of rocks with an accuracy of 89%, aerial images of lands with an accuracy of 82.3%, and satellite imagery with an accuracy of 83.5%. His successful application suggests that images of larger surface areas may pose as a more effective approach for classifying samples. However, when an image contains too much information, it confuses the system, which then consequently misclassifies the rock.

In the future, it would be ideal to study the effect of varying the resolution to further verify whether the system is scale invariant. The illustration below is an example of how the 256 x 256 resolution images can be reduced in size to 64 x 64 in size. The new image would then be applied back into the system to evaluate whether its robustness holds for varying ranges as the resolution is changed:

Figure 19: Illustration of varying samples' resolution to study the system's classification accuracy

Table 3's results show that the samples' Haralick outcomes are most often binned in the medium member function. This occasion occurs when most rocks have similar Haralick parameters and a few samples have an extremely high or low value that offsets the range. Table 3 illustrates that 3 pairs' member functions are assigned the same. For instance, gneiss (GN2) and greenschist (GS1) have the same highest member function for

all 7 parameters. Hence, it explains why the system is confused (shown in Table 5) and misclassifies gneiss (GN2) as greenschist (GS1). An explanation for why some samples have similar Haralick parameters, can be accounted for by the shadows and reflections that impose false positive or false negative detection. False positive detection occurs when the system detects a non-existent texture. For example: the application detects a texture when it is only a shadow covering the rock's surface. However, false negative is caused by high contrast when the system fails to detect a texture.

Introducing additional categories of member functions can further mitigate the issue. For example, as shown in Figure 20, the addition of two more member functions (i.e. Very Low and Very High member functions) to the system will enhance the outcome in better differentiating among the samples.

Figure 20: An illustration of using additional member functions

6 Chapter: Conclusion

To enhance productivity, there would be added benefit if geological investigation could be undertaken with minimum human assistance. Hence, Haralick's feature extraction calculation was an effective strategy to autonomously obtain quantitative textural information from the rock surfaces. The Bayesian classifier currently has an 80% classification accuracy. The main challenges to further improvement are the limited available member functions as well as the large variation between some samples.

In the future, with the expansion of sample points in the catalogue, the system's robustness will increase. This is done as new input is further catalogued which reduces the error estimate of the outcome. However, until more data has been sampled and catalogued, it is not certain whether it would be sufficient to rely on only the 7 Haralick textural features -as a mean to extract patterns from the surface of the rocks- for classifying future samples. Also in the future, it will be desirable to introduce additional complications to simulate a more realistic rover-based geological exploration mission. These complications could range from imaging rock from various angles and distances from the rover, hide the rocks under sands or dust, and vary the lighting to create reflections and shadow surrounding the samples.

As long as the rover is trained for the desirable mission, it is robust enough to adapt to its environment. This was proven when Haralick performed his classification testing on a micrograph, aerial, and satellite images (Haralick et al., 1973a). The capabilities were

further verified during my master's thesis research when I trained the system using samples of rocks instead. Also, the outcome of my dissertation research has proven that the system is applicable to a variety of fields such as: planetary exploration, mining robotics, underwater retrieval, and medical telerobotics. In underground mining, an autonomous rock classification system is desirable for reducing human exposure in hazardous environments, such as unstable rock faces. Underwater retrieval missions can be made easier using the system, so that the robot can autonomously assess the state of a shipwreck or an oil spill while keeping the crew out of harm's way. Additionally, the medical telerobotic operations are beneficial in enhancing the human-robot interaction. The critical method can be lifesaving, in the event that the expert medic is physically unable to perform the operation on the patient that is located in a hostile or inaccessible location. The autonomous classification system can further verify the medic's diagnostics, offering the doctor the confidence to perform the medical operation remotely. It is also useful feature if the medic performing the operation has hand tremor. In such event, the system will adjust the movement of the instruments to enhance dexterity of performing the operation, while reducing human errors.

Appendices

Appendix A : Photography Setup

The camera model used, the Canon PowerShot SD780IS, was chosen because of its availability at the time of the research project. Also because the use of higher resolution images taken by a more sophisticated camera is not available on exploration missions when the intent of the mission is to travel light and utilize the existing onboard hardware.

The shutter speed, acting like how fast the curtain will close, is the duration that the camera's shutter is kept open for the exposure process. The higher the duration of the speed, the slower the shutter will close and hence the camera will be more sensitive to motion. Choosing any shutter speed above 0.0167 seconds will require the camera to be mounted on a tripod. Alternatively for high speeds, the use of image stabilization applications is required to counteract the camera shake effect. Since the camera was mounted on a tripod and the samples were stabilized on a flat surface with no motion, a shutter speed of about 0.0333 seconds (one level more sensitive than the above mentioned threshold) was chosen to produce relatively crisp images.

Figure A.1 illustrates the relation between shutter speed and image resolution.

Figure A.1: Example of varying shutter speeds (Beginner Digital Photography, 2013).

Left: the fan was photographed at a shutter speed of 0.167 seconds and aperture of f/9.

Middle: the fan was photographed at a shutter speed of 0.025 seconds and aperture of

f/3.8. Right: the fan was photographed at a shutter speed of 0.0125 seconds and aperture of f/3.8. All three images were photographed with at ISO of 1250.

The aperture setting of the camera controls the opening of the lens' diaphragm. The wider the diaphragm's opening, the more light is exposed onto the CCD (charge-coupled device) through the camera lens. As a result, the depth of field (DoF) is larger, which makes subjects in farther distances appear in focus. Figure A.2 demonstrates the varying aperture settings.

Figure A.2: Varying aperture settings (Jenkinson, 2008)

Aperture is measured via a dimensionless variable f-stop, also known as focal ratio, which represents the ratio between the focal length and the diameter of the opening of the camera (Smith, 2007). The following equation represents this relationship:

$$(f - stop) = \frac{\text{focal length}}{\text{diameter of the entrance pupil}} \quad (\text{A.1})$$

The, f/5.6, setting was appropriate for an image taken outdoors on a cloudy day.

International Organization of Standardization (ISO) measures how sensitive the camera is to the light entering it. The higher the ISO, the more sensitive the camera to ambient lighting. High ISO setting is ideal for low lighting environments as the camera doesn't require flash to image the subject. Higher sensitivity, however, will result in grainier images as illustrated in Figure A.3.

Figure A.3: Varying ISO (Jenkinson, 2008)

Figure A.3 is clearly illustrating the trade-off of varying sensitivity to lighting with the smoothness of the image. As the camera becomes more sensitive to light, it is able to capture more reflections and other details but, at the same time, it also gradually produced grainier photos (Jacobson et al., 2000). For this project, the ISO was set to 125 as it was the lowest ISO setting that the camera could handle; the intent was to reduce image noise that would have an adverse impact on the results when extracting rock textures.

The Circle of Confusion (CoC) is used in photography to determine the desirable depth of field in an image, such that the image is acceptably sharp. For my experimental setup, I assigned the CoC to 0.030 mm as it is recommended for my camera's settings of 35mm sensor. Often, CoC is associated with the image's format; but in essence, the value depends on the viewing conditions (also known as visual acuity) as well as the preferable image enlargement (Merklinger, 1992).

The flash was turned off to eliminate unnatural lighting, and the image size was set to large, in order to collect as much data as possible. The auto zoom was also turned off to ensure that all images were photographed under the same settings. Moreover, since the objects were being photographed in close proximity to the camera and were relatively small in size, the camera mode was set to Macro to capture close-up photos.

Lastly, for calibration purposes, an 18% gray card was used prior to imaging of the rock samples to ensure that the colour balance remained consistent for the library of images. Also, to standardize the opacity of the images by avoiding reflective backgrounds that would result in false colouring of the objects, all samples were photographed on a green background. This is because green is one of the primary colours in computer vision, and hence will affect the opacity of a photograph.

Appendix B : Synthetic Examples Of Gray Level Co-Occurrence Matrices And Haralick Parameters

Figure B.1 shows three simple synthetic images featuring 4 stripes with different gray intensities, organized vertically, horizontally, and obliquely.

Figure B.1: Synthetic images of (a) vertical, (b) horizontal, and (c) oblique stripes with a resolution of 256 x 256 pixels. Intensities are 0 for black, 64 for dark gray, 128 for light gray, and 255 for white. Each horizontal or vertical stripe contains 16,384 pixels. The oblique image has 8,256 pixels for each the black and white stripes, 24,640 pixels for the dark gray stripe and 24,384 pixels for the light gray stripe.

The corresponding gray level co-occurrence matrices (GLCMs), computed using the scanning pattern shown in Figure B.2, are presented in Figure B.3. A total of 12 GLCMs (4 scans x 3 images) can be computed, however, in this case, only two different patterns emerge. The first pattern corresponds to images scanned at an angle that is non-

parallel to the directions of stripes (Figure B.3 left). However, the 90° scan of the vertical synthetic stripe results in the alternative GLCM outcome (Figure B.3 right).

Figure B.2: Scanning pattern. Each element in the GLCM is compared to its immediate neighbour along the horizontal axis (0° angle), the diagonal axis (45° angle), the vertical axis (90° angle) and the cross-diagonal axis (135° angle).

Figure B.3: (Left) GLCM for the vertical stripes image (Figure B.1(a)) scanned at angles 0° , 45° , 135° , the horizontal stripes image (Figure B.1(b)) scanned at angles 45° , 90° , 135° , and the oblique stripes image (Figure B.1(c)) scanned at angles 0° , 45° , 90° . (Right) Parallel scanning. GLCM for the vertical stripes image scanned at an angle of 90° , the horizontal stripes images at scanned at an angle of 0° , and the oblique stripes image scanned at an angle of 135° . Indices i and j correspond to grayscale intensities of adjacent pixels.

Table B.1 lists the Haralick parameters computed from the GLCMs of the 3 images shown in Figure B.1. The average for each parameter is the same regardless of the orientation of stripes (except for small discrepancies for the oblique image which does not have exactly the same number of pixels in each of the four stripes). Table B.1 demonstrate that averaged Haralick parameters are rotationally invariant.

Table B.1: Haralick parameters for the synthetic images shown in Figure B.1

		ASM	Contrast	Correlation	IDM	Entropy	Sum Average	Sum of Squares
Vertical Stripes	0 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	45 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	90 °	2.60E+05	0.00E+00	2.19E+04	1.02E+03	-2.45E+03	2.26E+02	2.20E+07
	135 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	avg	5.53E+05	9.30E+06	1.04E+04	1.02E+03	-5.22E+03	2.21E+02	4.25E+07
Horizontal Stripes	0 °	2.60E+05	0.00E+00	2.19E+04	1.02E+03	-2.45E+03	2.26E+02	2.20E+07
	45 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	90 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	135 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	avg	5.53E+05	9.30E+06	1.04E+04	1.02E+03	-5.22E+03	2.21E+02	4.25E+07
Oblique Stripes	0 °	4.56E+05	7.27E+06	8.13E+03	1.02E+03	-4.76E+03	2.18E+02	3.84E+07
	45 °	6.50E+05	1.24E+07	6.61E+03	1.02E+03	-6.14E+03	2.19E+02	4.94E+07
	90 °	4.56E+05	7.27E+06	8.13E+03	1.02E+03	-4.76E+03	2.18E+02	3.84E+07
	135 °	2.60E+05	0.00E+00	2.19E+04	1.02E+03	-2.45E+03	2.26E+02	2.20E+07
	avg	4.55E+05	6.73E+06	1.12E+04	1.02E+03	-4.53E+03	2.20E+02	3.70E+07

For additional analysis, 16 blocks of incrementally increasing gray scale intensity were placed next to each other (Figure B.4(a)) or organized randomly (Figure B.5(a)). Their GLCMs and Haralick outcomes were compared (Figure B.4(b), Figure B.5(b), Table B.2). Interestingly, contrast is the only parameter which is sensitive to the spatial distribution of the blocks of varying grayscale intensity.

Figure B.4: (top left) 16x16 grayscale variation. (top middle) GLCM of 16x16 grayscale variation 0° . (top right) GLCM of 16x16 grayscale variation 45° . (bottom left) GLCM of 16x16 grayscale variation 90° . (bottom right) GLCM of 16x16 grayscale variation 135° .

Figure B.5: (top left) 16x16 grayscale random variation. (top middle) GLCM of 16x16 grayscale random variation 0° . (top right) GLCM of 16x16 grayscale random variation 45° . (bottom left) GLCM of 16x16 grayscale random variation 90° . (bottom right) GLCM of 16x16 grayscale random variation 135° .

Table B.2: Haralick parameters for the synthetic images shown in Figure B.4 and B.5

		ASM	Contrast	Correlation	IDM	Entropy	Sum Average	Sum of Squares
16x16 grayscale variation	0 °	1.14E+06	6.39E+05	1.61E+04	4.09E+03	-1.26E+04	2.46E+02	1.18E+08
	45 °	1.23E+06	9.60E+06	1.21E+04	4.09E+03	-1.53E+04	2.46E+02	1.47E+08
	90 °	1.14E+06	9.02E+06	1.52E+04	4.08E+03	-1.26E+04	2.46E+02	1.15E+08
	135 °	1.23E+06	9.60E+06	1.21E+04	4.09E+03	-1.53E+04	2.46E+02	1.47E+08
	avg	1.18E+06	7.21E+06	1.39E+04	4.09E+03	-1.39E+04	2.46E+02	1.32E+08
16x16 random	0 °	1.14E+06	1.71E+07	1.44E+04	4.08E+03	-1.26E+04	2.42E+02	1.14E+08
	45 °	1.23E+06	4.11E+07	1.03E+04	4.08E+03	-1.53E+04	2.39E+02	1.42E+08
16x16 grayscale variation	90 °	1.14E+06	2.43E+07	1.35E+04	4.08E+03	-1.26E+04	2.38E+02	1.10E+08
	135 °	1.23E+06	4.08E+07	1.03E+04	4.08E+03	-1.53E+04	2.39E+02	1.42E+08
	avg	1.18E+06	3.08E+07	1.21E+04	4.08E+03	-1.39E+04	2.39E+02	1.27E+08

Appendix C : Catalogue of Results

Table C.1: Catalogue of ASM Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	8.47E+06	14.61	88.39	1.28
BA1	1.40E+07	0.05	21.18	82.00
BA2	9.07E+06	8.30	96.89	2.40
BA3	1.41E+07	0.04	18.56	84.65
DB1	5.13E+06	85.76	17.42	0.04
DR1	2.38E+06	99.12	1.11	0.00
GB1	9.64E+06	4.71	99.98	4.30
GR1	4.86E+06	88.93	14.07	0.03
GR2	4.76E+06	89.96	12.93	0.02
KM1	9.34E+06	6.32	99.05	3.19
PR1	1.52E+07	0.01	7.55	94.50
PR2	1.38E+07	0.06	24.36	78.67
PU1	8.86E+06	10.18	94.43	1.92
RH1	1.11E+07	1.00	83.77	18.08
RH2	8.99E+06	8.96	96.06	2.21
CK1	7.89E+06	24.20	76.19	0.69
CG1	8.98E+06	9.05	95.94	2.18
CG2	8.63E+06	12.67	91.04	1.51
CG3	7.05E+06	43.88	55.66	0.28
DL1	1.35E+07	0.08	28.44	74.26
LM1	9.03E+06	8.62	96.49	2.30
SD1	1.70E+07	0.00	1.11	99.12
SD2	1.40E+07	0.05	20.20	83.00
SH1	1.22E+07	0.31	57.70	41.73
GN1	2.90E+06	98.50	2.04	0.00
GN2	7.52E+06	32.15	67.32	0.47
GS1	8.35E+06	16.26	86.16	1.13
GY1	1.35E+07	0.08	29.12	73.51
SL1	1.49E+07	0.02	10.13	92.39
WL1	1.38E+07	0.06	23.33	79.76

Table C.2: Catalogue of Contrast Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	2.52E+07	4.47	100.00	4.53
BA1	1.13E+07	84.06	19.14	0.04
BA2	2.39E+07	6.93	98.46	2.90
BA3	1.25E+07	77.46	25.50	0.06
DB1	4.73E+07	0.00	1.61	98.79
DR1	4.83E+07	0.00	1.11	99.12
GB1	1.34E+07	71.85	30.62	0.09
GR1	2.74E+07	2.20	96.02	8.99
GR2	2.60E+07	3.54	99.54	5.71
KM1	2.04E+07	19.24	82.28	0.92
PR1	1.20E+07	80.38	22.74	0.05
PR2	8.30E+06	93.45	8.85	0.02
PU1	1.56E+07	55.08	45.44	0.18
RH1	1.94E+07	25.09	75.15	0.66
RH2	2.72E+07	2.33	96.61	8.52
CK1	2.49E+07	4.93	99.93	4.11
CG1	1.17E+07	81.92	21.26	0.05
CG2	1.32E+07	73.43	29.19	0.08
CG3	2.21E+07	12.09	91.83	1.59
DL1	1.23E+07	78.62	24.41	0.06
LM1	1.83E+07	32.69	66.76	0.46
SD1	4.74E+06	97.94	2.87	0.00
SD2	1.80E+07	35.14	64.22	0.41
SH1	2.17E+06	99.12	1.11	0.00
GN1	4.19E+07	0.02	9.37	93.03
GN2	1.99E+07	21.94	78.92	0.78
GS1	2.01E+07	20.79	80.33	0.84
GY1	3.57E+06	98.61	1.88	0.00
SL1	4.50E+06	98.10	2.63	0.00
WL1	1.03E+07	87.78	15.31	0.03

Table C.3: Catalogue of Correlation Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	1.85E+03	90.61	12.20	0.02
BA1	1.27E+03	95.92	5.68	0.01
BA2	2.42E+03	80.10	23.01	0.06
BA3	8.30E+02	97.91	2.91	0.00
DB1	2.83E+03	67.96	34.08	0.10
DR1	1.03E+04	0.00	1.11	99.12
GB1	1.25E+03	96.06	5.50	0.01
GR1	4.65E+03	11.34	92.87	1.71
GR2	6.68E+03	0.56	71.44	28.35
KM1	2.09E+03	86.97	16.17	0.03
PR1	3.03E+02	99.06	1.20	0.00
PR2	2.83E+02	99.09	1.16	0.00
PU1	2.43E+03	79.95	23.16	0.06
RH1	2.83E+03	68.07	33.99	0.10
RH2	3.65E+03	37.71	61.62	0.37
CK1	5.49E+03	3.42	99.40	5.89
CG1	3.34E+03	49.23	50.70	0.23
CG2	5.34E+03	4.25	99.97	4.76
CG3	1.86E+03	90.45	12.38	0.02
DL1	3.23E+03	53.36	46.97	0.19
LM1	1.73E+03	92.12	10.46	0.02
SD1	3.25E+03	52.73	47.54	0.20
SD2	9.44E+02	97.51	3.48	0.01
SH1	2.57E+02	99.12	1.11	0.00
GN1	5.95E+03	1.71	92.87	11.33
GN2	4.23E+03	19.73	81.66	0.90
GS1	4.93E+03	7.70	97.61	2.59
GY1	7.60E+03	0.14	39.22	62.13
SL1	8.11E+02	97.97	2.82	0.00
WL1	4.38E+03	16.33	86.07	1.12

Table C.4: Catalogue of IDM Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	1.51E+04	84.31	18.89	0.04
BA1	2.17E+04	1.39	89.76	13.60
BA2	1.93E+04	10.55	93.94	1.85
BA3	2.10E+04	2.67	97.84	7.50
DB1	1.18E+04	99.02	1.27	0.00
DR1	1.17E+04	99.12	1.11	0.00
GB1	2.20E+04	1.10	85.59	16.69
GR1	1.48E+04	87.37	15.74	0.03
GR2	1.53E+04	81.26	21.90	0.05
KM1	1.92E+04	12.01	91.95	1.60
PR1	1.91E+04	13.18	90.34	1.44
PR2	1.85E+04	20.47	80.73	0.86
PU1	1.91E+04	12.58	91.16	1.52
RH1	1.75E+04	37.26	62.07	0.37
RH2	1.52E+04	82.46	20.73	0.05
CK1	1.53E+04	81.70	21.47	0.05
CG1	2.44E+04	0.12	37.56	64.01
CG2	2.38E+04	0.22	50.03	49.96
CG3	1.66E+04	58.06	42.80	0.16
DL1	2.08E+04	3.19	99.06	6.31
LM1	1.84E+04	20.91	80.18	0.83
SD1	2.75E+04	0.01	4.98	96.45
SD2	1.69E+04	51.35	48.78	0.21
SH1	1.78E+04	31.88	67.61	0.47
GN1	1.17E+04	99.11	1.13	0.00
GN2	1.82E+04	24.71	75.60	0.67
GS1	1.91E+04	12.37	91.45	1.55
GY1	2.91E+04	0.00	1.11	99.12
SL1	2.21E+04	1.02	84.30	17.67
WL1	2.31E+04	0.41	64.47	34.89

Table C.5: Catalogue of Entropy Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	-2.06E+05	26.43	73.61	0.61
BA1	-2.26E+05	90.23	12.64	0.02
BA2	-2.03E+05	17.89	84.02	1.01
BA3	-2.31E+05	95.58	6.15	0.01
DB1	-1.77E+05	0.33	59.34	40.03
DR1	-1.46E+05	0.00	1.11	99.12
GB1	-2.10E+05	41.91	57.53	0.31
GR1	-1.79E+05	0.41	64.42	34.94
GR2	-1.80E+05	0.48	68.04	31.48
KM1	-2.10E+05	39.42	59.93	0.34
PR1	-2.25E+05	88.52	14.52	0.03
PR2	-1.98E+05	8.88	96.15	2.23
PU1	-2.10E+05	41.13	58.27	0.32
RH1	-2.21E+05	78.90	24.15	0.06
RH2	-2.07E+05	29.41	70.27	0.53
CK1	-1.80E+05	0.55	71.09	28.67
CG1	-2.10E+05	38.44	60.90	0.35
CG2	-2.04E+05	21.31	79.68	0.81
CG3	-2.00E+05	11.46	92.71	1.69
DL1	-2.22E+05	82.55	20.65	0.05
LM1	-2.12E+05	47.70	52.10	0.24
SD1	-2.42E+05	99.12	1.11	0.00
SD2	-2.30E+05	94.14	8.00	0.01
SH1	-1.49E+05	0.00	1.99	98.53
GN1	-1.58E+05	0.01	7.88	94.24
GN2	-1.99E+05	9.62	95.18	2.04
GS1	-1.96E+05	6.61	98.78	3.04
GY1	-1.85E+05	1.13	86.20	16.24
SL1	-1.97E+05	7.15	98.23	2.80
WL1	-2.31E+05	94.97	6.94	0.01

Table C.6: Catalogue of Sum Average Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	2.16E+02	5.73	99.52	3.52
BA1	1.92E+02	19.63	81.79	0.90
BA2	1.35E+02	87.00	16.13	0.03
BA3	1.59E+02	63.57	37.96	0.13
DB1	1.95E+02	17.13	85.02	1.06
DR1	2.37E+02	1.82	93.71	10.72
GB1	1.29E+02	90.68	12.13	0.02
GR1	2.47E+02	1.01	84.11	17.82
GR2	2.83E+02	0.12	37.31	64.30
KM1	1.99E+02	13.99	89.23	1.35
PR1	1.02E+02	97.91	2.91	0.00
PR2	9.00E+01	98.96	1.36	0.00
PU1	2.20E+02	4.73	99.98	4.28
RH1	2.91E+02	0.08	28.34	74.37
RH2	3.10E+02	0.03	13.47	89.48
CK1	2.97E+02	0.06	22.98	80.13
CG1	2.07E+02	9.23	95.70	2.14
CG2	2.50E+02	0.86	80.72	20.48
CG3	1.85E+02	27.22	72.72	0.59
DL1	3.17E+02	0.02	9.67	92.78
LM1	1.89E+02	22.66	78.03	0.75
SD1	3.07E+02	0.03	15.16	87.92
SD2	1.89E+02	23.00	77.62	0.74
SH1	8.69E+01	99.12	1.11	0.00
GN1	2.26E+02	3.38	99.34	5.97
GN2	2.64E+02	0.37	61.81	37.53
GS1	2.41E+02	1.40	89.87	13.52
GY1	3.54E+02	0.00	1.11	99.12
SL1	1.54E+02	69.40	32.81	0.10
WL1	3.54E+02	0.00	1.12	99.12

Table C.7: Catalogue of Sum of Squares Parameter

Rock Sample	Data	Low Member Function (%)	Medium Member Function (%)	High Member Function (%)
AN1	1.52E+09	29.24	70.46	0.53
BA1	1.20E+09	60.32	40.81	0.15
BA2	7.14E+08	91.66	11.00	0.02
BA3	8.37E+08	86.93	16.21	0.03
DB1	1.32E+09	48.23	51.61	0.24
DR1	1.98E+09	5.87	99.42	3.44
GB1	6.13E+08	94.31	7.78	0.01
GR1	2.03E+09	4.90	99.94	4.13
GR2	2.65E+09	0.40	63.78	35.57
KM1	1.32E+09	48.41	51.45	0.24
PR1	3.24E+08	98.18	2.52	0.00
PR2	2.35E+08	98.72	1.71	0.00
PU1	1.61E+09	21.88	78.98	0.79
RH1	2.74E+09	0.29	55.91	43.61
RH2	3.09E+09	0.07	26.16	76.75
CK1	2.61E+09	0.48	68.07	31.45
CG1	1.47E+09	33.91	65.49	0.43
CG2	2.10E+09	3.75	99.73	5.40
CG3	1.14E+09	65.97	35.84	0.11
DL1	3.04E+09	0.08	29.71	72.85
LM1	1.18E+09	61.81	39.50	0.14
SD1	2.88E+09	0.16	42.34	58.58
SD2	1.11E+09	68.19	33.88	0.10
SH1	1.42E+08	99.12	1.11	0.00
GN1	1.74E+09	14.13	89.03	1.33
GN2	2.29E+09	1.73	93.09	11.17
GS1	2.05E+09	4.52	100.00	4.49
GY1	2.96E+09	0.11	35.68	66.16
SL1	5.97E+08	94.65	7.36	0.01
WL1	3.96E+09	0.00	1.11	99.12

Appendix D : Member Function Plots

Figure D.1: Member Function of ASM

Figure D.2: Member Function of Contrast

Figure D.3: Member Function of Correlation

Figure D.4: Member Function of IDM

Figure D.5: Member Function of Entropy

Figure D.6: Member Function of Sum Average

Figure D.7: Member Function of Sum of Squares

Appendix D : Catalogued Images Of The 30 Rock Samples

PU1_11

PU1_12

PU1_13

PU1_21

PU1_22

PU1_23

RH1_11

RH1_12

RH1_13

RH1_21

RH1_22

RH1_23

RH2_11

RH2_12

RH2_13

RH2_21

RH2_22

RH2_23

CK1_11

CK1_12

CK1_13

CK1_21

CK1_22

CK1_23

CG1_11

CG1_12

CG1_13

CG1_21

CG1_22

CG1_23

CG2_11

CG2_12

CG2_13

CG2_21

CG2_22

CG2_23

CG3_11 CG3_12 CG3_13 CG3_21 CG3_22 CG3_23

DL1_11 DL1_12 DL1_13 DL1_21 DL1_22 DL1_23

LM1_11 LM1_12 LM1_13 LM1_21 LM1_22 LM1_23

SD1_11 SD1_12 SD1_13 SD1_21 SD1_22 SD1_23

SD2_11 SD2_12 SD2_13 SD2_21 SD2_22 SD2_23

SH1_11 SH1_12 SH1_13 SH1_21 SH1_22 SH1_23

Figure E.1: Catalogued rock images

Appendix E : Uncatalogued Images Of The 23 Rock Samples

Figure F.1: Uncatalogued rock images

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