

Optimizing Exomars Pancam Multispectral Science: Investigating the Limits of Material Classification



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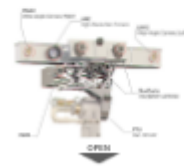
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Introduction

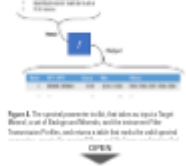
We are developing tools for investigating how spectral parameters can be optimally extracted and combined to maximize the overall performance of the instrument against its operational background.
This work supports the development of intelligent algorithms to support the PanCam Wide-Angle Camera (WAC) [1] of the ExoMars Trace Gas Orbiter (TGO) [2] and perform active Oxide Planet landing site [3].
These multi-parameter algorithms will contribute to the ongoing efforts of the landing site selection campaign, towards the ultimate objective of identifying an optimal landing site, and determining the presence of biogeochemicals.

PanCam

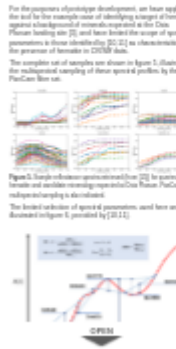


The Toolkit Pipeline

Spectral Parameters
Spectral parameters are a set of statistical values that are used to describe the spectral characteristics of a material. The dimension reduction method is often used to both visualize and reduce the dimensionality of the data required to make a particular observation.
Spectral parameters have been used effectively with a total of over 1000 spectral images from the Mars Reconnaissance Orbiter (MRO) [4] in preparing for PanCam. This data set is available in the form of a PanCam data set, which is a set of data files that can be used to generate a PanCam data set.



Example Study: Hematite at Oxia Planum



Linear Discriminant Analysis

We evaluate the ability of each spectral parameter combination to discriminate between two particular mineral and a background set with Linear Discriminant Analysis (LDA) [5]. LDA finds the linear combination of a set of spectral parameters that maximizes the separation between the target and background classes, while minimizing the variance within each class.
The transformation from each spectral parameter x_i using a_i to the combination y_i is given by:
$$y_i = \sum_{j=1}^n a_{ij} x_j$$

The result is a score that indicates the success of that spectral parameter combination in discriminating between the two classes.
Conclusions and Future Work
With the development of a number of algorithms, we have shown that it is possible to improve the accuracy of the instrument by including component level details of the spectral sampling of the complete system, including the time and space dependent, and observation dependent accuracy (e.g. illumination conditions and detector noise level).
As present spectral parameters are defined in advance to generate the profiles, the complete combination of spectral parameters for the standard operations of [2] will be required.

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INTRODUCTION

We are developing a tool for investigating how spectral parameters can be optimally captured and combined to maximise the contrast between a defined target material against an expected background.

This work supports the planning of multispectral imaging campaigns that the PanCam Wide-Angle Cameras (WACs) [1] of the ESA-Roscosmos ExoMars Rosalind Franklin rover [2] will perform at the Oxia Planum landing site [3].

These multispectral images will contribute to the mapping efforts of the landing site mineral composition, towards the mission objectives of characterising an ancient habitat, and determining the presence of biosignatures.

PANCAM

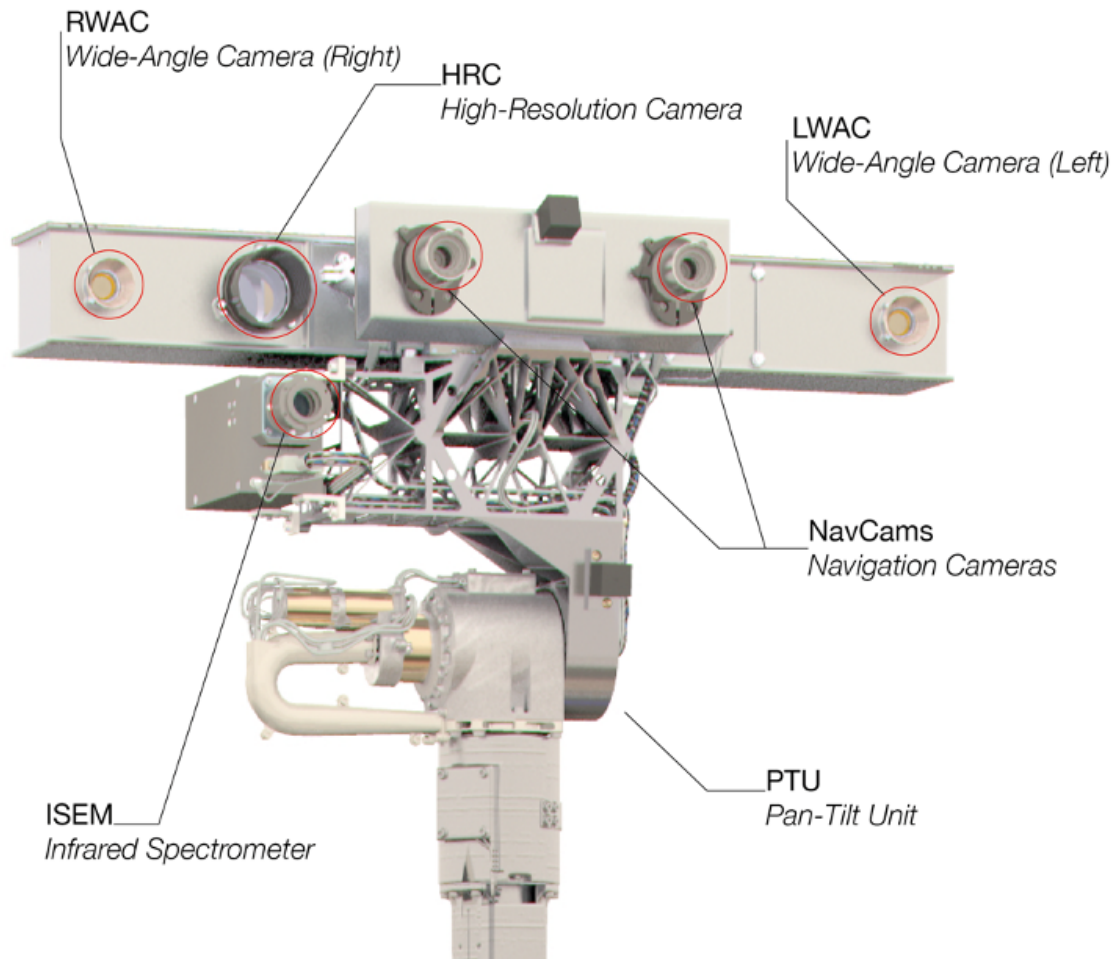


Figure 1. Visualisation of PanCam mounted on the rover mast Pan-Tilt Unit, hosting the WACs and HRC. Also mounted are the NavCams and ISEM.

PanCam (figure 1) [1] is the mast-mounted multispectral stereo panoramic camera system for the ExoMars Rosalind Franklin rover [2], with a primary objective of visually characterising the geology of the landing site.

The system is mounted on the rover mast at a height of ~2m, and consists of 3 cameras; a stereo pair of multispectral Wide Angle Cameras (WACs), and the long-focus colour High Resolution Camera (HRC).

PanCam is comparable to the multispectral imaging systems of current and past Mars rovers (M2020 Mastcam-Z [4], MSL Mastcam [5] and MER Pancam [6]).

Of the 22 filters hosted by the PanCam WACs, 12 narrowband geology filters have been selected, chosen by the PanCam Science Team to sample the VNIR reflectance of the martian mineralogy with minimal error [7], with profiles shown in figure 2.

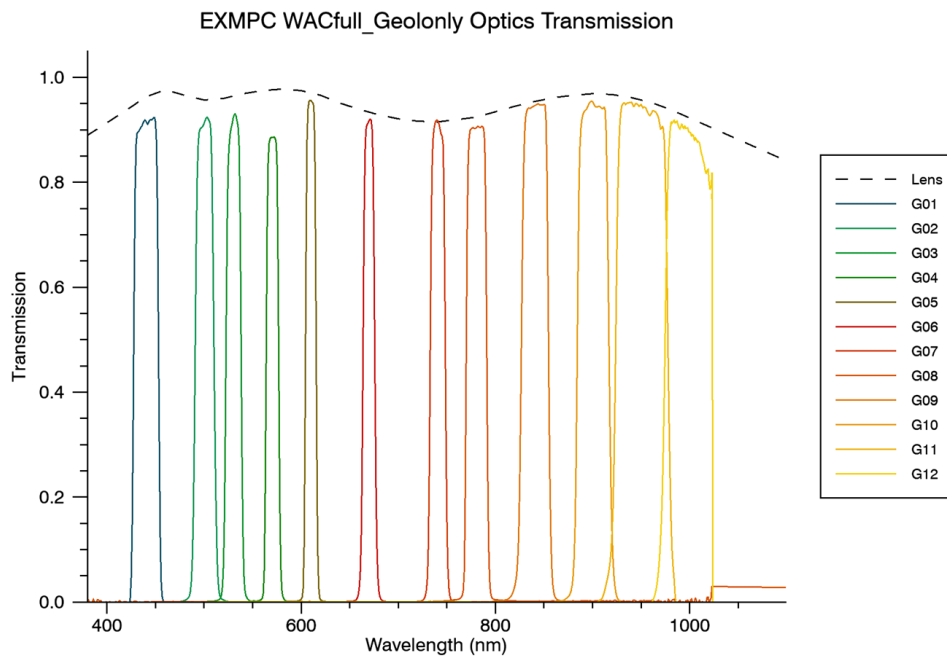


Figure 2. The spectral transmission profiles of the 12 narrowband geology filters of the WACs.

THE TOOLKIT PIPELINE

Spectral Parameters

A spectral parameter is an operation that acts on a spectrum and returns a measure of a certain feature, such as the depth of an absorption or the gradient of a slope (see fig. 6). This dimension reduction method is effective for both visualising multispectral image stacks, and minimising the data required to make a particular observation.

Spectral parameters have been used effectively with orbital and rover spectral imaging data for Mars exploration [8,9,10,11,12]. In preparing for PanCam, this literature is invaluable. However, the spectral sampling of PanCam is distinct from past and present systems [13], justifying a quantitative re-assessment of the problem.

The Pipeline

The goal of this study is to produce a tool, as a command-line interface written in Python, that achieves the function illustrated in figure 4.

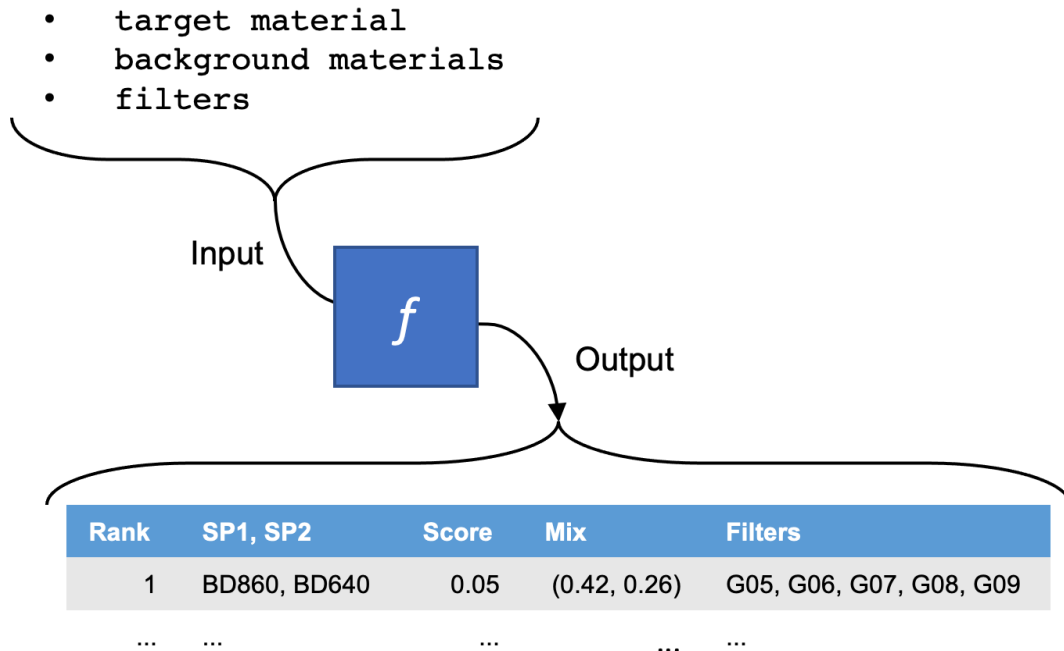


Figure 4. The spectral parameter toolkit, that takes as input a Target Mineral, a set of Background Minerals, and the instrument Filter Transmission Profiles, and returns a table that ranks the valid spectral parameters, reports the required filters, and the linear combination that maximises target/background contrast.

The stages of the computation are as follows:

1. Get mineral reflectance spectra of target and background materials

Reflectance spectra matching the queried target and background material lists are sought from a spectral library database. Currently, we use the Western Washington University Vis-NIR Spectroscopy Database (<http://spectro.geol.wvu.edu/>) as a standardised source of a number of widely used spectral libraries [14].

2. Sample the material reflectance spectra with the filter transmission profiles

The expected reflectance observed by each filter of transmission profile $T_F(\lambda)$ is computed, according to:

$$R_{F,M} = \frac{\int_{\text{VNIR}} T_F(\lambda) R_M(\lambda) d\lambda}{\int_{\text{VNIR}} T_F(\lambda) d\lambda}$$

3. Compute the Spectral Parameters

For the given filters, all valid spectral parameters are computed, limited to four classes, defined by the expressions illustrated in figure 6, of Band Depth (BD), Shoulder Height (SH), Ratio (R) and Slope (S) [10,11].

4. Evaluate the Target/Background separation achieved by each spectral parameter, and all pairwise combinations

The ability of a spectral parameter, or pair combination of spectral parameters, to separate a target from a background is computed with the method *Linear Discriminant Analysis* [15] (top right panel).

5. Rank the Spectral Parameters and combinations by separation score

The information is collected and formatted into the output table (table 1), ordered by LDA separation score.

EXAMPLE STUDY: HEMATITE AT OXIA PLANUM

For the purposes of prototype development, we have applied the tool for the example case of identifying a target of hematite against a background of minerals expected at the Oxia Planum landing site [3], and have limited the scope of spectral parameters to those identified by [10,11] as characteristic of the presence of hematite in *CRISM* data.

The complete set of samples are shown in figure 5, illustrating the multispectral sampling of these spectral profiles by the PanCam filter set.

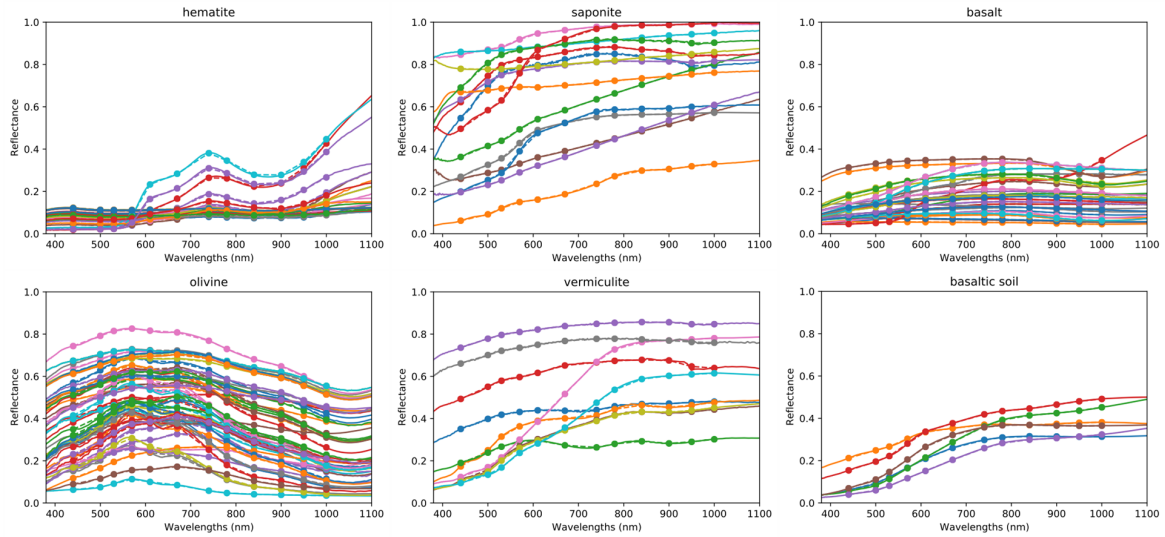


Figure 5. Sample reflectance spectra retrieved (from [15]) for queries of hematite and candidate mineralogy expected at Oxia Planum. PanCam multispectral sampling is also indicated.

The limited selection of spectral parameters used here are illustrated in figure 6, provided by [10,11].

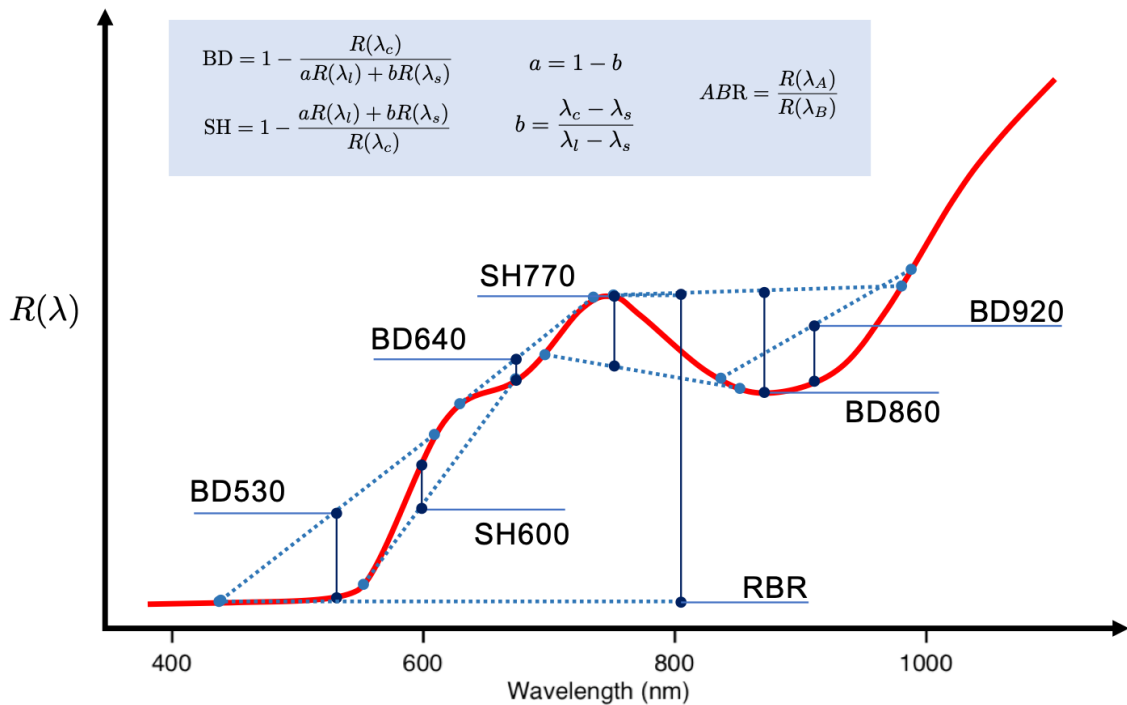


Figure 6. Spectral parameters identified by [12,13] suitable for the identification of hematite in *CRISM* hyperspectral data, used in this pilot study.

We have visualised the distribution of the spectral parameter values of each material-labelled sample in paired scatterplots (fig. 7), to provide visualisation of the clustering and separation of target and background sample classes.

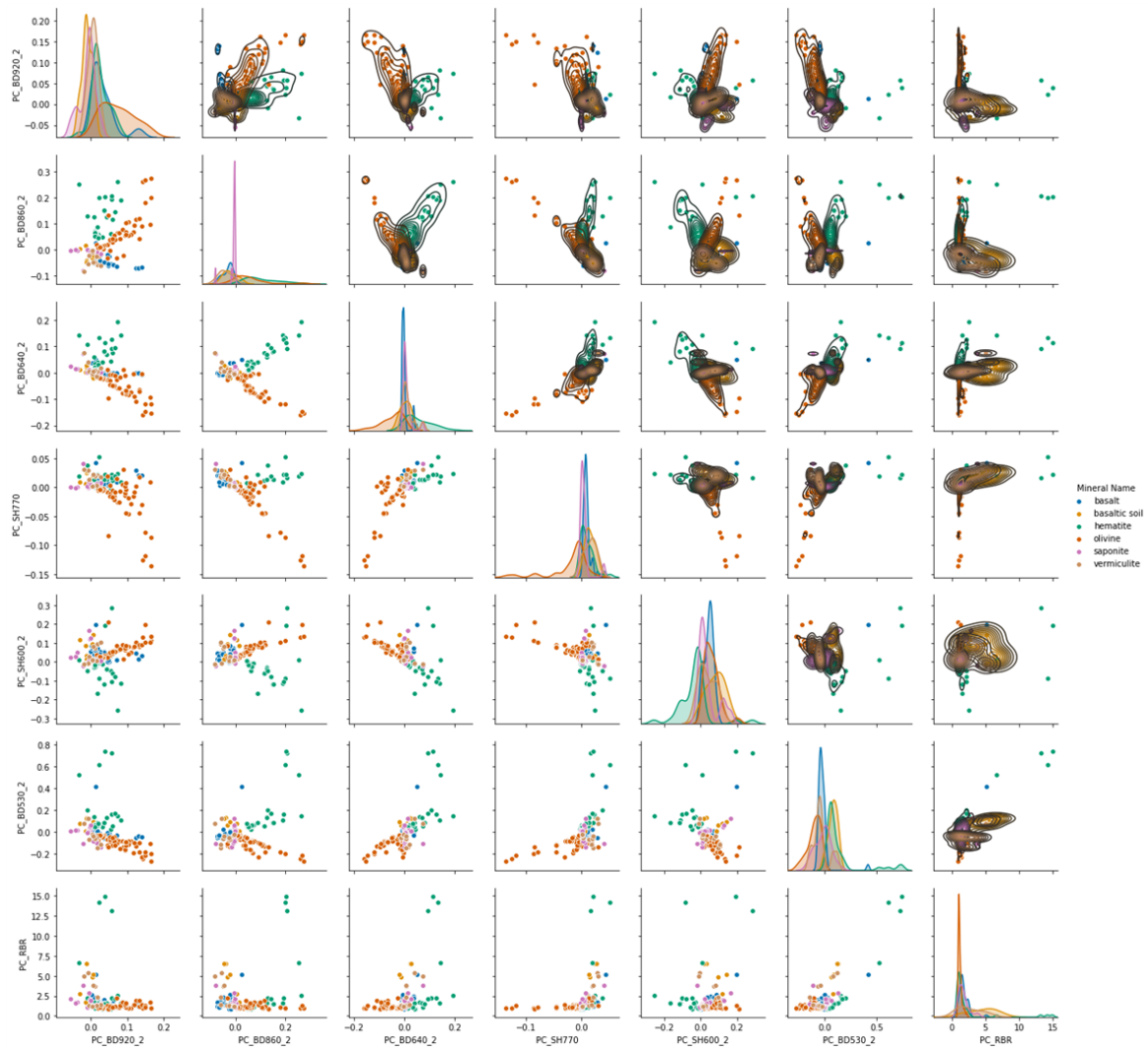


Figure 7. Paired scatterplots of the spectral parameters (SPs), indicating the data distribution of hematite (green) against background minerals (other colours) across the SP vector space. Univariate plots (diagonal) indicate single SP discrimination, whilst bivariate plots indicate the advantage of combining SPs. Upper triangle gives density contours to the same plots.

Figure 8 illustrates the result of a Linear Discriminant Analysis fit on an example spectral parameter combination. The routine has found the mixture of optimal separation, illustrated by the red line.

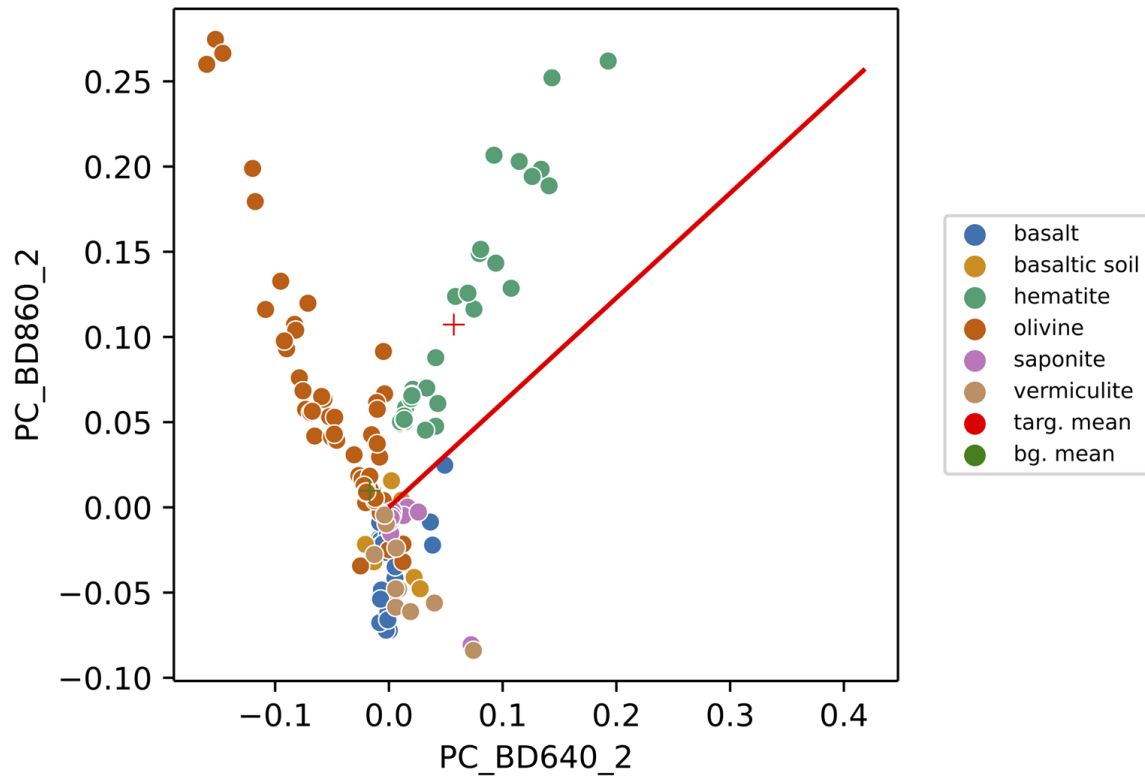


Figure 8. Linear Discriminant Analysis on a pair combination of spectral parameters, illustrating the separation of hematite (green) from background (other) samples.

The resultant ranking of the spectral parameter pair combinations is given by table 1. Note, that in the top ten scores, there are no single spectral parameters, only paired combinations. This implies that for the detection of hematite, multiple spectral parameters are preferable to single spectral parameters.

Table 1. Visualisation of PanCam mounted on the rover mast Pan-Tilt Unit, hosting the WACs and HRC. Also mounted are the NavCams and ISEM.

Rank	Spectral Parameters	Score
1	PC_BD860_2,PC_BD640_2	0.05603
2	PC_SH770,PC_BD860_2	0.04372
3	PC_BD530_2,PC_SH600_2	0.04368
4	PC_SH600_2,PC_BD860_2	0.04094
5	PC_RBR,PC_BD530_2	0.03865
6	PC_BD860_2,PC_BD530_2	0.03474
7	PC_BD920_2,PC_BD860_2	0.02980
8	PC_BD640_2,PC_SH770	0.02895
9	PC_SH600_2,PC_BD640_2	0.02450
10	PC_BD640_2,PC_BD530_2	0.02385
11	PC_BD920_2,PC_BD640_2	0.02254
12	PC_SH600_2,PC_RBR	0.02183
13	PC_RBR,PC_BD640_2	0.01970
14	PC_BD640_2	0.01907
15	PC_SH770,PC_BD530_2	0.01902
16	PC_BD920_2,PC_BD530_2	0.01897
17	PC_BD530_2	0.01812
18	PC_BD860_2,PC_RBR	0.01460
19	PC_SH600_2,PC_BD920_2	0.01456
20	PC_SH770,PC_SH600_2	0.01453
21	PC_SH600_2	0.01453
22	PC_BD860_2	0.01417
23	PC_RBR,PC_SH770	0.00200
24	PC_BD920_2,PC_RBR	0.00163
25	PC_SH770,PC_BD920_2	0.00158
26	PC_SH770	0.00151
27	PC_RBR	0.00112
28	PC_BD920_2	0.00076

LINEAR DISCRIMINANT ANALYSIS

We evaluate the ability of each spectral parameter combination to discriminate between one particular material and a background set with Linear Discriminant Analysis (LDA) [15]. LDA finds the 1D projection, denoted \mathbf{a} , of a 2D spectral parameter combination that maximises the separation between the target and background clusters, whilst minimising the variance of each of these clusters.

The transformation from each spectral parameter, sp_1 and sp_2 to the combination $sp_{1,2}$ is given by:

$$sp_{1,2} = \mathbf{a}^T \mathbf{sp}$$

$$sp_{1,2} = [a_1, a_2] \begin{bmatrix} sp_1 \\ sp_2 \end{bmatrix}$$

The result is a score that indicates the success of that spectral parameter combination, that can be used as a ranking. The score is the Fischer Linear Discriminant,

$$J(\mathbf{a}) = \frac{|\mathbf{a}^T (\bar{\mathbf{s}}^t - \bar{\mathbf{s}}^b)|^2}{\mathbf{a}^T \mathbf{S}_w \mathbf{a}}$$

that acts on the means of the pre-labelled clusters of the target and background sample classes, and the scatter matrix (\mathbf{S}_w) that gives the total scatter (estimated covariance) of each class. Thus the score J is the ratio of mean separation to class variance. The line \mathbf{a} is found analytically from the data.

A variant of the LDA method has been investigated for autonomous classification of rock types in RGB colour images [16].

CONCLUSIONS AND FUTURE WORK

With the pipeline initiated, a number of expansions are planned.

There is scope to improve the accuracy of the instrument model, by including component level details of the spectral sampling of the complete system (e.g. including the lens and detector response), and observation dependent uncertainty (e.g. illumination conditions and detector temperature).

At present, spectral parameters are defined in advance; to generalize the pipeline, the complete combinatorial space of spectral parameters, for the standard operations of [10,11], will be explored.

In addition to quantitative assessment, the success of the spectral parameter as a qualitative tool can be investigated, in terms of the target-background contrast achieved in an image product. This is achieved by synthesizing spatial scenes of the target and background, via environment/imaging simulation software [17], and by processing the resultant images through the ExoSpec toolkit, a multispectral image analysis software package for ENVI, developed by the PanCam science team [18].

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