

# Optimising Image Acquisition and Post-Processing with the ExoMars PanCam Wide Angle Camera Simulator

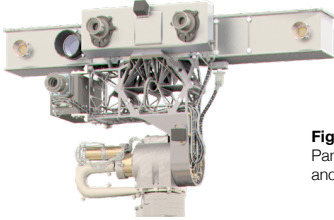
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## 1. Introduction

**Context:** PanCam<sup>1</sup> is a 3 camera system for the ExoMars rover<sup>2</sup>, featuring a pair of Wide Angle Cameras (WACs), for 3D stereo vision and multispectral imaging, and a High Resolution Camera (HRC), for close-up colour imaging.



**Figure 1:** CAD Model of PanCam, also hosting NavCam and ISEM. Credit: ESA

**Motivation:** Quantitative processing of PanCam data (e.g. 3D reconstructions, photometric studies) benefits from maximal Signal-Noise Ratios (SNR). SNR in digital photography is influenced by:

- Scene properties: e.g. Illumination, contrast (due to composition)
- Intrinsic camera properties: e.g. gain, dark signal coefficients
- Extrinsic camera properties: e.g. temperature, exposure time
- Post-processing: e.g. calibration, statistical noise-removal

In this study, we present a method for exploring this parameter space, to find command and post-processing sequences that will optimise the final image product SNR.

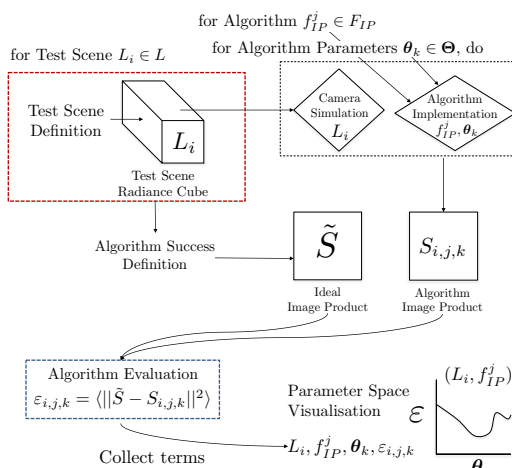
## 2. Problem Statement

Optimising over all properties listed above presents a combinatorial explosion problem. E.g., if the properties of illumination, scene contrast, exposure time, calibration and noise removal were each represented by a single 8-bit parameter, there would be  $1 \times 10^{12}$  possible combinations. It is not practical to collect experimental data on this scale with laboratory hardware.

**Proposed Solution:** We resolve this in part by implementing the problem computationally, enabled by a comprehensive simulation of the PanCam WACs<sup>3</sup>, and the extensive database of images of the Mars surface collected by the MER Pancam experiment<sup>4</sup>.

## 3. Simulated Algorithm Evaluation

The general method for testing an algorithm is illustrated here.



**Figure 2:** Simulated Algorithm Evaluation signal chain

1. A set of test scenes is defined, as hyperspectral image radiance cubes.
2. An 'ideal' image product is defined from the test scene, based on the algorithm objectives.
3. A trial algorithm is selected from the set of suitable algorithms, and a list is generated of all possible parameter combinations.
4. Iteratively, a synthetic image is acquired via the WAC simulator, for all parameters
5. Synthetic images are compared to the ideal examples via a cost-function.
6. Cost-minimisation then guides the selection of optimal algorithms and parameter combinations.

## 4. Example: Auto-Exposure Optimisation and Evaluation

We apply this method to the evaluation of an auto-exposure algorithm for the PanCam WACs.

### Problem Formulation

First we define the algorithm objectives and parameters, and introduce the test scenes.

### Auto-Exposure objective:

Find the optimal exposure time for a given scene and given filter.

### Generic Algorithm:

1. Acquire image at 'Seed' (initial guess) exposure time
2. Evaluate image by a chosen statistic
3. Evaluate observed statistic to a 'Target' criteria
4. Rescale previous exposure, according to  $\text{target:observed}$  ratio
5. Iterate until ratio is within tolerance, or iterations exceed a threshold

### Test Scenes:

We parameterise test scenes with the continuous variable of illumination, and discretise scene composition into 4 classes: *Ground*, *Ground+Sky*, *Ground+Calibration-Target*, and *Solar*. Example scenes and illumination values were taken from the MER Pancam data record<sup>6</sup>.

### Defining Ideal Image Products:

'Optimal' image exposure is subjective, dependent on the radiance of the object of interest. We define an 'optimal' image by manually selecting the brightest object of interest, and analytically find the exposure that would map that radiance level to our 'Target' Statistic value.

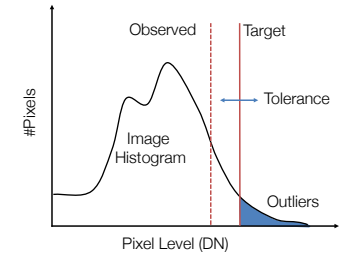
### Trial Algorithm: Histogram Fitting

**Statistic:**  $n^{\text{th}}$  Percentile Pixel Level (DN), where  $n$  is user defined.

(This algorithm is used by MER cameras<sup>5</sup>)

### Algorithm parameters (abbrev.):

- Seed Exposure (*Seed*)
- Target Statistic Value (*Target*)
- 1-Percentile (*Outliers*)
- Tolerance (*Tol.*)
- Threshold # Iterations (*Max. Iters.*)

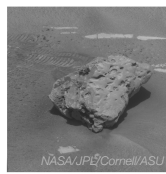


**Figure 3:** Illustration of Auto-Exposure, adapted from [5]

### Parameter Quantisation:

For the presentation of this method we have sampled a subset of the parameter space, acquiring synthetic images for: 4xComposition Classes, 3xIllumination steps, 128xTarget steps, 128xOutlier steps, 64xSeed steps,  $>1 \times 10^7$  images in total.

## Illustrative Results and Discussion



Ground Class Test Scene

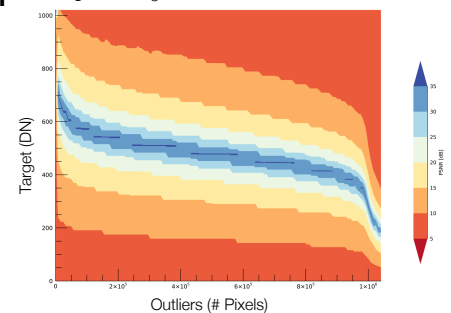
**Data Visualisation:** The most challenging part of the analysis is choosing a suitable representation of this high-volume dataset and high-dimensional cost function. Here, we show results, from a single *Ground* class scene.

### Interpreting Peak-SNR Plots:

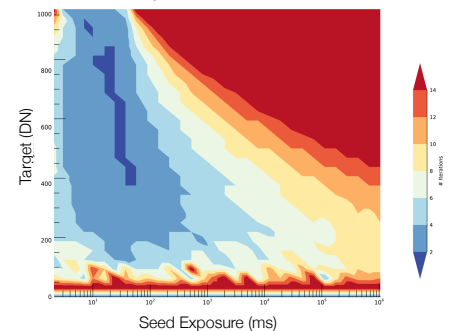
For visualisation, we group properties in pairs. Statistical parameters *Target* and *Outliers* are displayed here for a fixed *Seed*, as a contour plot of the 128x128 peak-SNR values (top-right). The blue strip represents high Peak-SNR, clearly displaying the optimal region for these parameters, under the given conditions. We see that a well selected *Target* level, in this case, ~500DN, affords a wide range of satisfactory *Outlier* values. The extension of this study will be to explore the combined results for all combinations.

**Improving the method:** We found that the Peak-SNR metric was not always the most suitable. The *Seed* parameter only effected the final image quality when causing *Max. Iters.* to be exceeded. We found that a count of iterations used in a sequence was a more discriminatory cost-metric, displayed here for varied *Target*, with *Outliers* set optimally according to the results above.

**Figure 4:** Target vs Outliers P-SNR



**Figure 5:** Target vs Seed Exposure Iterations



## 5. Conclusions and Future Work

### In summary, we have:

- demonstrated how camera simulation can enable high-resolution ( $>1$  million samples) algorithm parameter space investigations.
- presented a general form of the method.
- illustrated how this can help identify optimal parameter settings, with an example of Auto-Exposure.

### Future Work

- Visualisation and evaluation of the high-dimensional cost-function remains challenging – we are investigating convex optimisation methods to apply to this.
- For validation, we have collected laboratory observations for a subset of the parameter space, using the PanCam Engineering Model, currently under analysis.

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### References

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