Spacecraft Material Characterization Using Reflectance Spectra Extracted from RGB/IR Color Images

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Outline

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- Experimental setup
- Machine Learning
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  - Machine learning algorithm (RBF network)
  - Training procedure for algorithm
  - Model Validation
- Conclusion


Photo credit: NASA


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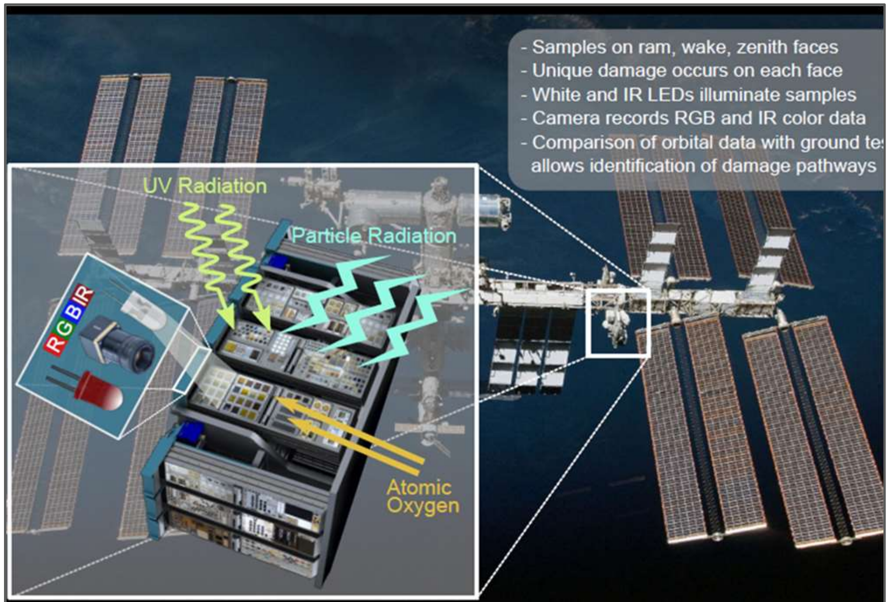
Motivation

- Thorough knowledge of how material properties evolve throughout the mission helps to improve reliability of spacecraft
- Development of correlation between true space exposure and accelerated space weather aging experiments at ground facilities enables accurate prediction of on-orbit material performance



ISS images by courtesy of www.nasa.gov

Several novel and heritage materials sent to ISS as part of MISSE-16 mission and changes in spectral reflectivity monitored as a result of exposure to different low Earth orbit (LEO) environment.

Ground Experiments

- After deploying MISSE-16 mission receive red, green, blue and infrared (RGB/IR) images for 6 months
- RGB/IR color data will be first of its kind and allow as to observe the progression of space weather changes to materials in real time
- Replica of the hardware installed in the JUMBO space irradiation chamber at SCICL AFRL
- Materials will be exposed to electrons and VUV and reflectance data collected using the same lighting and parameters as used on MISSE-16

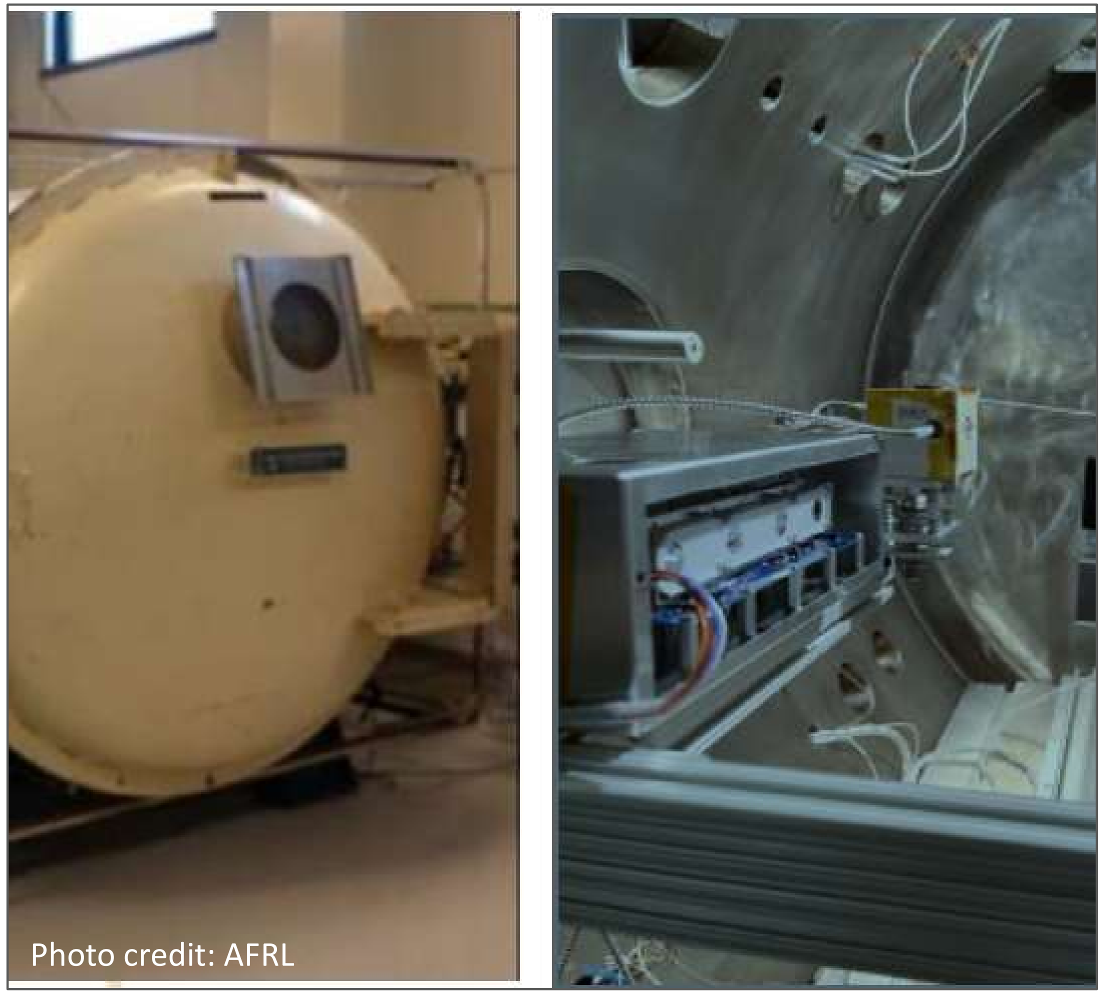


Photo credit: AFRL

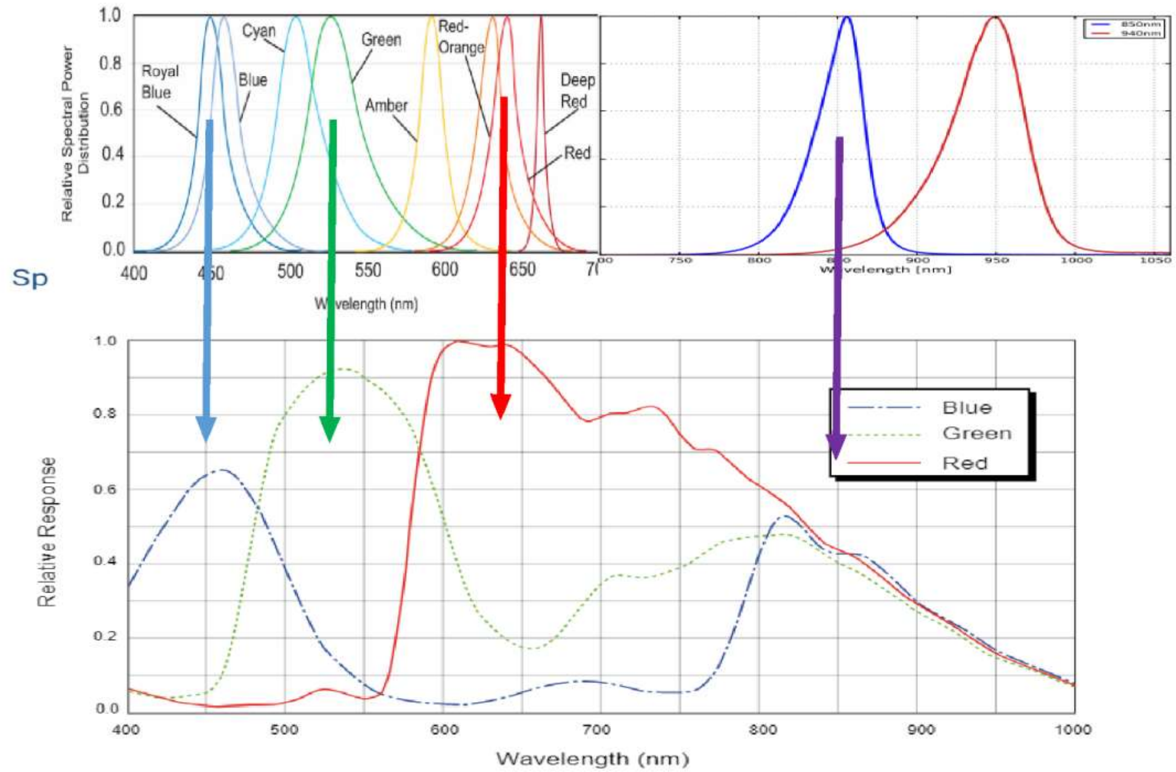
"Spacecraft materials degradation under a space simulated low Earth orbit (LEO) environment" by Dr. Elena Plis

Camera Response

Photo credit: AFRL

Lights

Camera



https://www.baslerweb.com/en/products/cameras/area-scan-cameras/ace/aca2440-20gc/

Basler daA1600-60uc camera with IR LED illumination that provides broad illumination ranges in IR region

Machine Learning

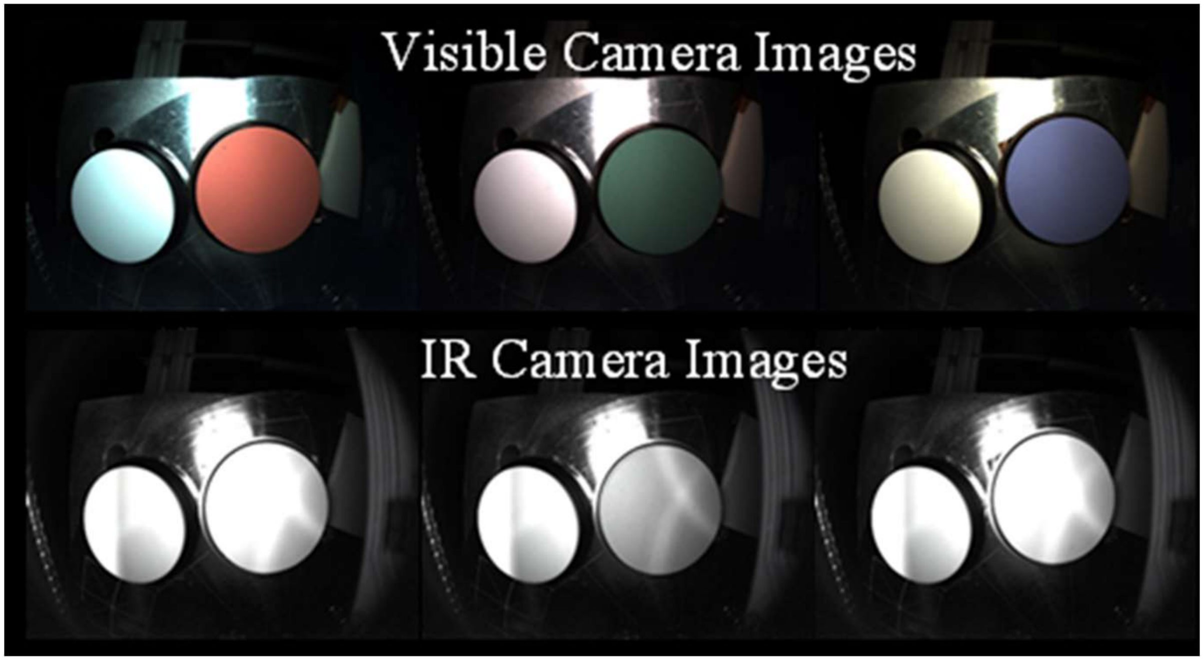


Image credit: AFRL

Color and IR images of Spectralon color standards which have a well characterized reflectance spectra were collected with the MISSE camera to calibrate the machine learning algorithm

Machine Learning

- Visible and IR images as well as Directional Hemispherical Reflectance (DHR) spectra were collected for the pristine materials in the JUMBO vacuum chamber
- The materials were then exposed to electrons and VUV irradiation and color, IR images and DHR spectra collected every hour

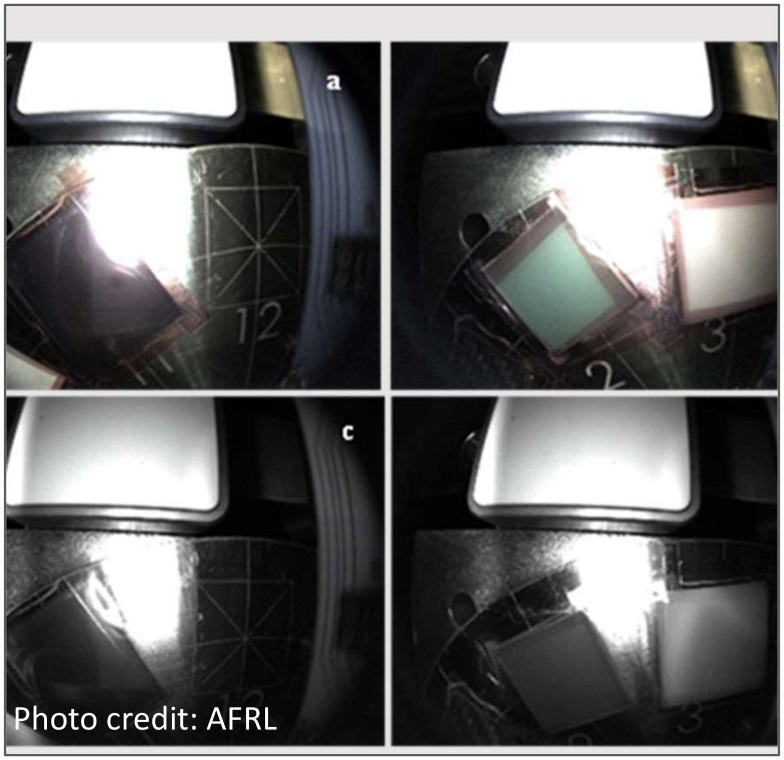
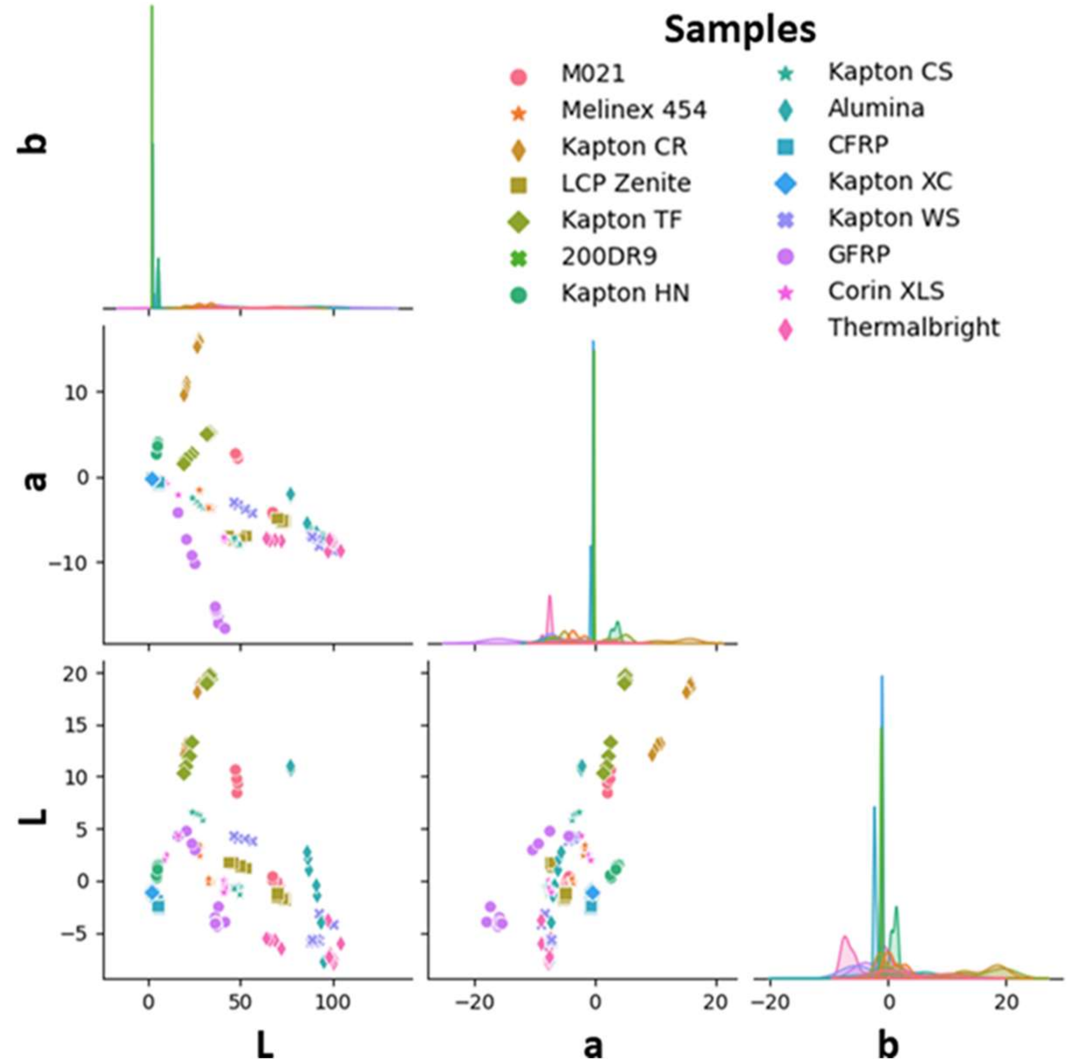


Photo credit: AFRL

- As the materials are subjected to electrons and VUV irradiation the optical properties change
- DHR spectra along with the RGB/IR camera images will be used to train machine learning algorithm

Machine Learning

- Spectral characterization from camera is an under constrained problem since it involves mapping from a low dimensional space (RGB/IR pixel counts) to a high dimensional space (reflectance as a function of wavelength)
- Use machine learning approach that uses a radial basis function (RBF) network
- RBF network is used for non-linear interpolation of sparsely spaced data
- Our dataset is also non-uniformly distributed within our chosen color space



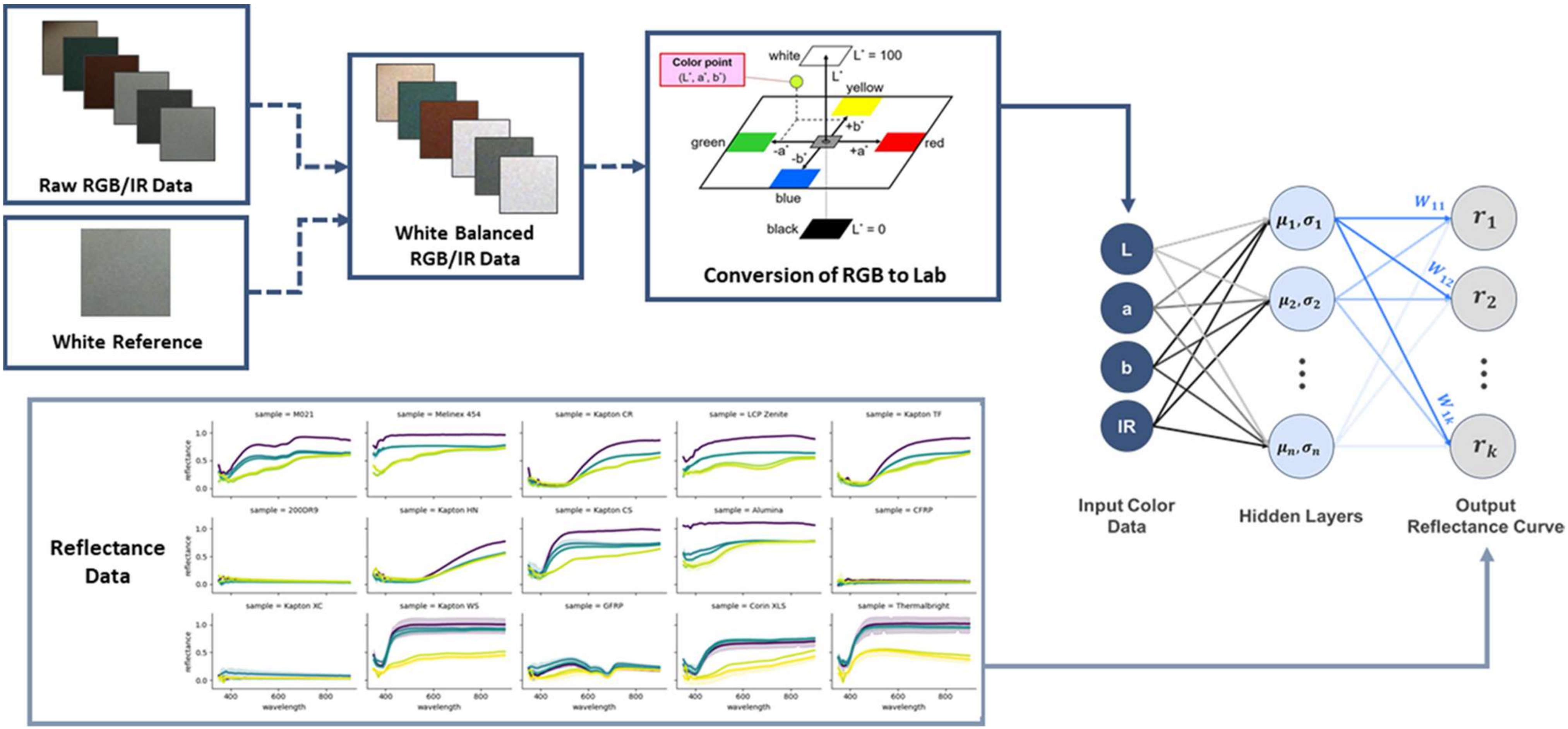
Spectral characterization from camera is an under constrained problem

Machine Learning – RBF network

- RBF model is mapping (f) between input color data and spectral reflectance data
- Mapping is denoted by $f: R^4 \rightarrow R^k$, where 4 denotes the 4 color channels (L*a*b* and IR) and k denoted the number of spectral channels with k > 4
- $f(x) = \omega_0 + \sum_{1=1}^{M} \omega_i \phi\left(\frac{\|x-\mu_i\|}{\sigma_i}\right)$
- A custom Keras layer representing this RBF node was written in order to learn the trainable parameters (μ_i, σ_i and ω_i) via standard backpropagation algorithm approaches

Radial basis function (RBF) network used for the Machine Learning Algorithm

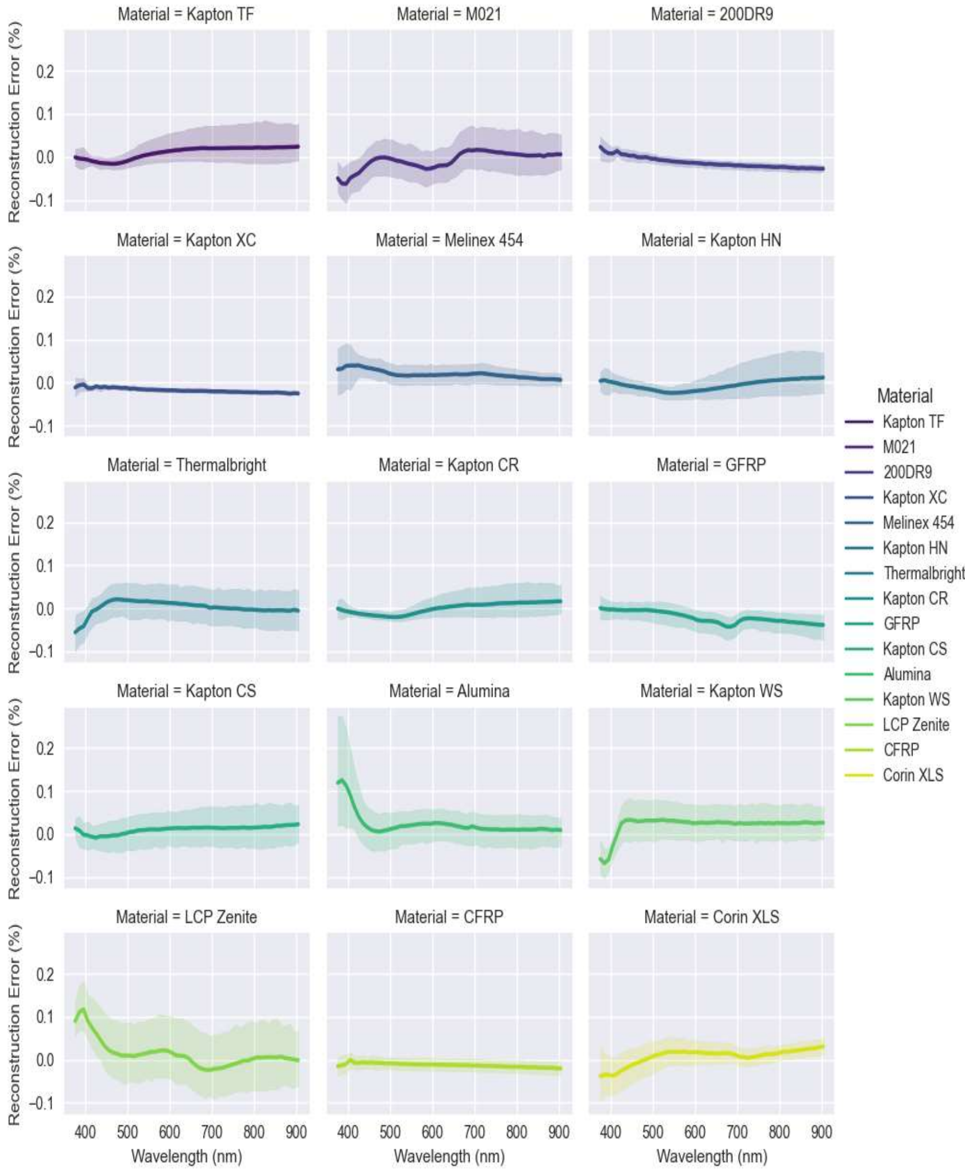
Training Procedure



The Machine Learning Algorithm will give an estimated reflectance spectrum for each image

Model Validation

- Model was trained on 140 samples of color (L*a*b* and IR) and spectral information
- Validation was done on approximately 70 samples of color (L*a*b* and IR) and spectral information. There was a 2/1 split in the training and validation datasets respectively
- Dark lines represent mean reconstruction error and transparent bars represent the spread of the error
- Model is able to retrieve the spectrum to within 10% error for the majority of samples across wavelengths 350nm to 900nm
- Lowest overall error is near the green (500nm) and red (650nm) wavelength regions and highest overall error occur in the blue (400nm) region.



Conclusion

- Correlation of MISSE data with extensive ground testing of flight duplicate samples under simulated space weather conditions will enable development of fundamental chemical models for material degradation
- A detailed predictive knowledge of space weather-induced material color change will enable robust and accurate space domain awareness by allowing remote observers to glean knowledge about a spacecraft by examining the spectral signature of unresolved images
- The RBF network machine learning algorithm was developed and validated for ground testing of MISSE materials after exposure to electron and VUV. The model is able to retrieve the spectrum to within 10% accuracy for most materials
- Next steps are to apply the machine learning algorithm developed using ground testing to the images from the MISSE-16 mission

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QUESTIONS?