https://ntrs.nasa.gov/search.jsp?R=20190033263 2019-12-26T01:28:48+00:00Z

Machine Learning Approaches to Data Reduction from the MapX X-ray Fluorescence Instrument for Detection of Biosignatures and Habitable Planetary Environments

Richard C. Walroth[1] , David F. Blake[1], Philippe Sarrazin[2], Franck Marchis[2], and Kathleen Thompson[2],
[1]Exobiology Branch, MS 239-4, NASA Ames Research Center, Moffett Field, CA 94035
(richard.c.walroth@nasa.gov).
[2]SETI Institute, Mountain View, CA 94043.

Introduction: The search for evidence of life or its processes involves the detection of biosignatures suggestive of extinct or extant life, or the determination that an environment either has or once had the potential to harbor life. *In situ* elemental imaging is useful in either case, since features on the mm to µm scale reveal geological processes which may indicate past or present habitability. The Mapping X-ray Fluorescence Spectrometer (MapX) is an *in-situ* instrument designed to identify these features on planetary surfaces (Sarrazin, 2016). Here we present progress on instrument development, data analysis methods, and element quantification.

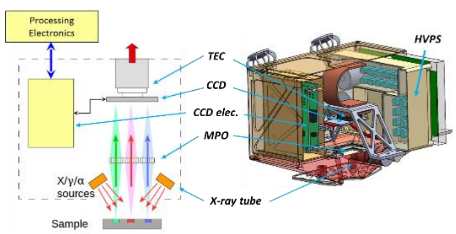

Figure 1. Left: Schematic representation of MapX. Right: Rendering of the arm mounted instrument in a flight like configuration.

Instrument Description: Figure 1 shows a schematic of the instrument, which consists of X-ray sources, a focusing optic, and a CCD. Either radioisotope (e.g., ^{244}Cm) (Radchenko, 2000) or X-ray tube sources can be used. The focusing lens is an X-ray micro-pore optic (MPO) which focuses X-rays 1:1 onto the CCD. The MPO has a large depth of field, allowing rough unprepared surfaces to be imaged with minimal resolution loss (~1 cm with a nominal lateral resolution of 100 µm). The CCD is exposed and read at a rate of several frames per second, allowing the x, y position and energy of each photon to be recorded. Summing multiple frames yields XRF spectra for each individual pixel.

Data Analysis: The images collected by the CCD are binned by energy and combined into an x, y, energy data cube, the size of which will make downlinking of the raw data infeasible. Obtaining photon energy maps at the characteristic energies of different elements from the data cube is straight forward. However, these maps do not provide precise elemental composition information because different characteristic lines can overlap and background effects cannot be easily subtracted. Using machine learning, regions of similar composition can be identified based on the rough element maps mentioned above. The XRF spectra for these ROI can be summed to generate high signal to noise spectra for ground processing.

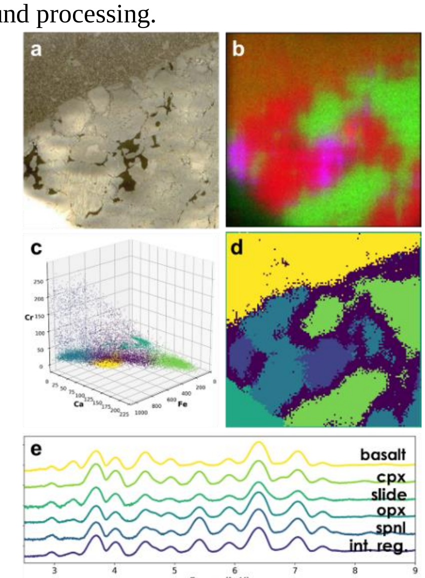

Figure 2. a) Optical image of a petrologic thin section of an ultramafic xenolith imaged with MapX-2 prototype (field of view, 15 mm). b) False color image, Fe = red, Ca = green, and Cr = blue. c) Correlation between Fe, Ca, and Cr as a 3D scatter plot. d) Labels applied to the 2D image showing the locations of the different ROI. e) Summed spectra from the different ROI with assigned mineralogy (cpx: clinopyroxene, slide: glass slide, opx: orthopyroxene, spnl: spinel, int. reg.: interfacial regions).

Acknowledgements: This work was supported by the Ames Center Investment Fund (CIF), NASA's PICASSO (13-PICASSO-0111) and MatISSE (16-MATISE16_2-0005) programs, and the NASA Postdoctoral Program.

References: Radchenko, V. et al. *Applied Radiation and Isotopes* 53 (2000), 821-824.
Sarrazin, P. *et al.* (2016) *LPSC XLVII* #2883.