INSTRUMENT SCIENCE AUTONOMY FOR ORBITAL AND FLYBY PLANETARY MISSIONS.

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Introduction: Spacecraft instruments today can do more than passively collect and transmit data. Onboard data analysis and autonomous response enable the capture of dynamic or short-lived events as well as increasing overall mission science return. These capabilities have been developed and demonstrated for a variety of spacecraft. This abstract describes capabilities for orbital and flyby missions; autonomous science for surface missions is described in [1].

Orbital or flyby planetary missions may operate at great distances from the Earth. Communications are limited by the speed of light as well as the fact that the Deep Space Network is a resource that is shared by all active planetary missions. Onboard data analysis can enable instruments to exploit gaps between communication opportunities and make better use of available downlink volume by identifying features of interest to inform data prioritization, generating compressed data summaries, or filtering out poor quality data. Instruments can also automatically collect additional observations or alert other instruments to an event of interest (cross-instrument coordination). Next we describe examples of current instrument science autonomy capabilities and how they could apply to future instruments.

Surface feature detection: To detect known features of interest, we can train a machine learning classifier with labeled examples and then deploy it to analyze new data as it is collected. For example, we trained a classifier to detect tiny sulfur deposits on top of arctic glaciers as a proxy for the kind of microbial biosignatures that could potentially manifest on Europa [2]. The classifier operates on data collected by Hyperion, a pushbroom hyperspectral imager on the EO-1 Earth orbiter. The study region (Borup Fiord) is considered one of the best Europa analog sites on Earth. We used the trained classifier on EO-1 to monitor the seasonal appearance and disappearance of sulfur deposits from orbit [3] (see Fig. 1).

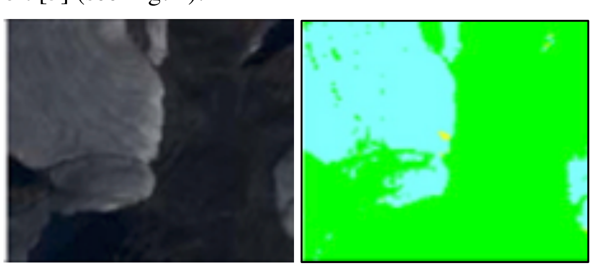

Fig. 1. Supraglacial sulfur deposits (marked in yellow) detected by a classifier onboard the EO-1 Earth orbiter [3].

We also devised a statistical method that can detect and track the seasonal CO_2 and water ice caps on Mars using THEMIS infra-red images collected by the Mars Odyssey orbiter [4]. This method separates image regions into CO_2 ice, water ice, and defrosted terrain. It could potentially be used by thermal imagers studying icy bodies such as Europa, Ganymede, and Enceladus to characterize ice composition and potentially identify slightly warmer regions where the ice crust has thinned. These areas are of great astrobiological interest.

Detection of dynamic or short-lived events: Onboard analysis of instrument data is perhaps best motivated when the goal is to detect dynamic or short-lived events, such as plumes from Enceladus or Europa. We developed an algorithm to detect and track emissions from moons or irregularly shaped bodies (asteroids, comets) in real-time to enable fast follow-up and characterization [5]. The algorithm uses a convex hull model to distinguish the body under observation from any emitted material. We tested this approach on 756 Cassini ISS-NAC images of Enceladus, in which it detected 49 real plumes and 22 false positives. Most of the false positives (77%) came from poor quality or non-limb images which should be filtered out prior to this analysis. We also applied plume detection to 45 EPOXI MRI images of comet Hartley 2, which has an irregular shape and multiple active jets. The largest jet was correctly identified and localized in every image. Example results are shown in Fig. 2.

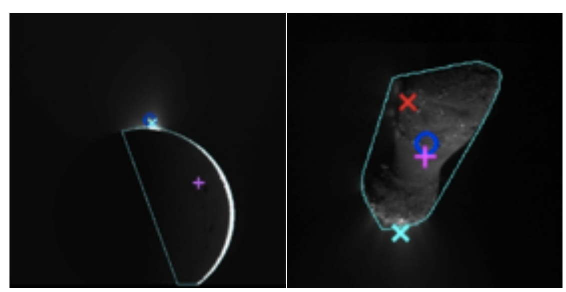

Fig. 2. Automated plume detection (cyan x) for Enceladus (left) and comet Hartley 2 (right) [5]. Other markers are for competing methods that did not perform as well.

Data quality filtering: Assessing data content prior to its transmission to Earth can also yield operational benefits by filtering out low-quality data and thereby reducing the volume of data to be transmitted. The IPEX Earth orbiting CubeSat used a trained classifier to determine cloud cover so that images in which the surface is visible receive higher priority [6]. An example result from its onboard deployment is shown in Fig. 3.

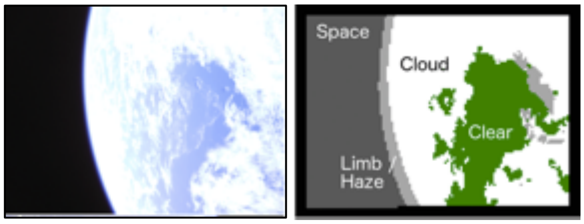

Fig. 3. Onboard classification of IPEX CubeSat Earth image regions into space, limb, cloud, and clear to prioritize cloud-free images. [6]

IPEX had only low-resolution commercial cameras onboard. We have re-trained the cloud classifier to operate on high-resolution (30 m/pixel) Hyperion data, and we are currently in the process of uploading this algorithm to the EO-1 Earth orbiter. Imaging instruments on a Titan balloon could employ the same technology to prioritize images that capture surface features over those that are obscured by haze.

Novelty detection: Training a machine learning algorithm to detect relevant surface or atmospheric features requires advance knowledge and several examples of the feature of interest. However, planetary missions aim to explore and characterize bodies for which our knowledge in incomplete. They may discover new phenomena or processes that manifest in ways we cannot predict in advance. The ability to detect novel or unexpected features is especially relevant to the search for life. We previously developed a novelty detector for imaging instruments that calculates the visual *salience* of each region within an image. Onboard IPEX, it identified three small lakes in Tibet despite no prior training or guidance about bodies of water [7]. Hydrocarbon lakes on Titan could be detected in a similar fashion. We are uploading this algorithm to EO-1 as well.

Monitoring: Some science objectives focus not on particular features but instead on continuous monitoring of an atmospheric or environmental property. One example is the aerosol opacity of the Mars atmosphere. We devised a regression algorithm to estimate the dust and water ice content of the atmosphere from THEMIS data [8]. Like most imaging instruments, THEMIS is able to collect more data than it can downlink. By running this algorithm onboard Mars Odyssey, we would obtain much greater temporal and spatial coverage of the Mars atmosphere instead of being restricted to only those frames transmitted to Earth. We also envisioned operational scenarios in which a high opacity detection (potentially indicating the formation of a dust storm or the presence of a water ice cloud) would trigger the transmission of a subset of the full THEMIS data centered on that location. The opacity estimation algorithm predicted ice opacity with an RMSE of 0.016, well within the uncertainty in the reference model (0.040). Dust opacity (see Fig. 4) was more challenging (RMSE 0.087) because atmospheric dust can be easily confused with surface dust, but it was sufficiently reliable to detect potential dust storms. Similar atmospheric monitoring would be valuable for a Titan orbiter.

Lessons learned and recommendations for future instruments: Future instrument development will benefit most from autonomous science by integrating it into the initial instrument design and test plans to ensure that relevant science objectives are addressed and resource constraints (memory, computation, response time) are met. It is also vital to characterize the impact of operating on uncalibrated data and identify any necessary adjustments (e.g., we employed an empirical calibration for THEMIS data to compensate for temperature drift of the focal plane array that corrected ice temperature measurements by about 15 K [4]).

References: [1] Francis R. et al. (2016) *3rd Workshop on Inst. for Planet. Miss.* (this meeting). [2] Mandrake, L. et al. (2012) *ACM TIST 3*, A77. [3] Gleeson, D.F. et al. (2010) *Remote Sens. Env. 114*, 1297-1311. [4] Wagstaff, K.L. et al. (2008) *Planet. & Space Sci. 56*, 256-265. [5] Wagstaff, K.L. et al. (2014) *ApJ 794*. [6] Altinok, A. et al. (2016) *J. of Field Robotics, 33*, 187-204. [7] Chien, S. et al. (2016) *J. of Aero. Inf. Sys.* [8] Castaño, R. et al. (2007) *13th KDD*.

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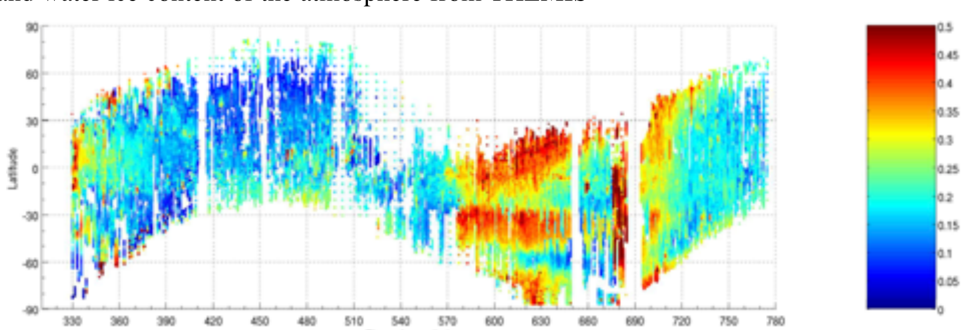

Fig. 4. Estimation of atmospheric dust opacity from Mars Odyssey THEMIS data as a function of time of year (Ls) and latitude [8]. Regional dust storms appear from Ls 580-650.