Onboard Science Data Analysis: Implications for Future Missions

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Summary

Onboard science data analysis will improve the capabilities of existing sensors and enable transformative new operational modes to address novel science issues. Two missions illustrate the trend: the Mars Exploration Rovers (MER) and the Earth Observer 1 spacecraft (EO-1). MER software autonomously interprets collected science data to identify features of interest such as clouds and dust devils. It responds by prioritizing data for downlink to Earth [10]. The EO-1 orbiter recognizes transient events and anomalies such as volcanic activity and responds with followup measurements [12]. In general, onboard analysis can improve science yield by relieving constraints on time, bandwidth and power, and by responding automatically to events on short time scales.

Autonomy will advance rapidly in coming years due to progress in the fields of artificial intelligence, robotics, computer vision, and machine learning. We recommend the panel support technology development to exploit these advances. Previously NASA programs such as ASTEP and AISRP have played a key role in advancing autonomous science data analysis. Growing resources for technology development will help planetary science benefit from advances in AI research. We also recommend recognizing autonomous onboard analysis in plans for future missions. Planning early for onboard analysis will ease infusion into future missions and enhance these instruments' science yield. This document summarizes the potential impact of some specific onboard data understanding systems. We will describe applications to rover, aerobot, and orbital platforms.

Rover and Lander Science

Automatic Target Detection and Response Improves Science Yield

Thanks to improvements in rover mobility, onboard data understanding could benefit rover platforms for potential Mars Sample Return (MSR) or Mars Astrobiology Field Laboratory (AFL) missions. Recent decades have seen significant progress in daily traverse ranges. Terrain analysis, visual odometry, and path planning algorithms permit Mars Exploration Rover (MER) spacecraft to navigate tens of meters autonomously [30, 7]. Terrestrial tests demonstrate kilometer-scale traverses through Mars analog terrain [49, 5, 18, 19]. Here rovers travel beyond the local visible horizon to survey large areas and visit multiple geologic units in a single command cycle.

Onboard science data analysis can exploit these kilometer-scale operations by identifying new science targets near the rover path and executing opportunistic followup measurements [38, 11, 40]. This enables fast traverse without sacrificing our understanding of the terrain visited *en route*. Over-the-horizon operational modes could benefit potential MSR and AFL objectives by quickly characterizing regional diversity in composition, morphology, and sedimentology over large geographic areas. These approaches hold promise for astrobiology investigations since evidence of potential habitats may be geographically isolated and invisible from orbit [5, 48].

Rovers can recognize science features for opportunistic sensor deployment [22, 38, 10]. Recent work has demonstrated fully automatic onboard target detection algorithms that recognize geomorphological features and anomalies [17, 43, 50]. Pattern recognition has automated a growing portfolio planetary geology tasks. These include detecting and classifying rocks [22, 17, 6], identifying anomalous outcrop [22, 38, 43], and characterizing sediment [44].

After its expected upload to the Mars Exploration Rovers, the AEGIS system will apply these techniques to support the Meridiani cobble campaign (Figure 1 A,B). AEGIS identifies targets in MER NavCam images and matches them against desired feature profiles provided by scientists. Scientists can configure AEGIS to target specific features, for example making it seek eccentric rocks with high albedo. The system responds with high-resolution subframed PanCam images of the most promising targets.

AEGIS typifies autonomous science systems that favor a particular class of important features or minerals that are set by scientists in advance [40, 4, 50, 17]. However, scientists cannot always anticipate the features that the rover might encounter. Alternative modes include *representative sampling* that automatically categorizes the data into archetypal classes and sends back salient examples of each class [9, 25]. Alternatively, *anomaly detection* seeks out statistical outlier features that are unlike any yet encountered [9, 43]. Statistical and machine learning methods for anomaly detection are common in industrial applications [1, 27], and these techniques transfer naturally to autonomous science target selection.

Followup measurements can take the form of high-resolution full-filtered images [17], remote reflectance spectroscopy, or thermal emission spectroscopy. Field tests with rover-mounted spectrometers have demonstrated the collection of dozens of spectra per command cycle from rocks that were detected with no human intervention [6]. Contact spectroscopy is also possible thanks to new single-cycle instrument placement techniques that can place instruments with minimal human guidance [35, 36, 50]. The ability to detect new targets, collect spectroscopy on the fly, and return to the scripted mission plan could be a transformative new option for long-range travel in potential MSR and AFL missions.

Finally, research has also demonstrated onboard planning and scheduling systems that can make context-sensitive followup decisions to balance the science value of the new data against mission objectives. This permits opportunistic reaction to targets of opportunity while simultaneously considering immediate and long-term goals related to resource usage and end-of-day position [41, 10, 50].

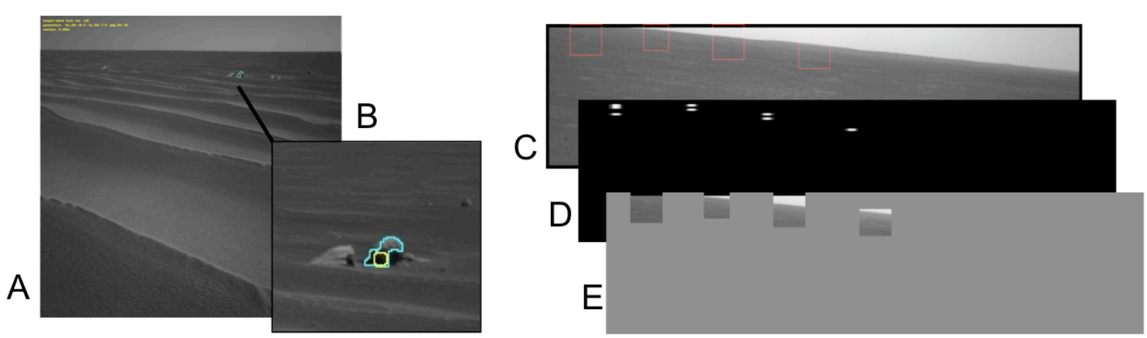

Figure 1: Automatic Onboard Image Analysis for MER Platforms. A) Automatic target detection using the AEGIS system. B) Target detail. C) Dust devil tracking across four NavCam frames. D) Summary data product, ~3KB size. E) Thumbnail images of dust devils. Images courtesy NASA/JPL/Cornell.

Selective Data Return Alleviates Bandwidth Constraints

Thanks to improvements in sensor resolution, science data volumes already outpace our ability to communicate the relevant measurements to Earth. There is a compelling case for rover data products such as high-resolution cameras and video that have even larger data rates. These products can benefit both science (to resolve fine features) and public outreach (to better realize a virtual "presence" through high-definition images and video). It is likely that we are entering a new phase of planetary exploration in which communications bandwidth becomes a key science bottleneck. Future rovers must reduce the vast data set of potential collected data to a manageable volume for transmission over the Deep Space Network.

Onboard analysis can relieve bandwidth constraints in several ways. First, spacecraft can collect large datasets that are subsampled using feature detection and prioritization to ensure that the most informative data products are transmitted. This can effectively multiply the science value of long traverses, enabling true survey modes that return representative images from geologic boundaries [42] or the main terrain types encountered during a traverse [11]. In addition, onboard data understanding permits spacecraft to summarize observations using more abstract descriptions. For example, mineral detection based on machine learning can automatically interpret and summarize spectral measurements [4, 21, 34]. Adaptive image compression can preserve fidelity in areas of high scientific interest [47].

Selective data return can unlock the temporal domain by recognizing and reacting to changes in the rover's environment. This is particularly poignant in the case of dust devils since they are rare and difficult to capture by chance. Recently, the WATCH system aboard the Mars Exploration Rovers demonstrated automatic selective data return that monitored image sequences to detect dust devils and transmit these images. Figure 1 (C,D,E) shows the result of dust devil tracking on a series of four NavCam images. Automatic detection produces a summary bitmask that reduces bandwidth requirements by orders of magnitude, and thumbnail images can provide validation images of the dust devil with little additional cost [11]. The WATCH system has already run successfully on Mars for several years, enabling atmospheric studies that would have been impossible otherwise due to onerous bandwidth requirements.

Selective data return can benefit future missions by increasing the effective science yield of high rate image sequences. Selective return of key frames and transition points in video [25, 42] could be used to subsample potential AFL and MSR navigation sequences, summarize flyby sequences for deep space operations or small bodies investigations, or identify the least-redundant images to transmit during EDL maneuvers. WATCH-style temporal change detection could certainly benefit a potential Titan lander, significantly improving science return at little mass or power cost.

Aerial Vehicles

Airships or balloons at Titan could cover orders of magnitude more terrain than that reachable by rovers. On Titan, an aerial perspective could resolve small-scale morphological features to investigate precipitation and liquid erosion processes [29], providing a dramatic counterpoint to our experience on Earth where with these phenomena dominate surface geology. Autonomous balloons at Venus could sample extensive vertical and horizontal profiles and address distinctive issues such as cloud structure, noble gas ratios and atmospheric superrotation.

Most Titan and Venusian mission concepts presume significant wind currents and high ground-relative speeds [15]. This means that an aerobot could cross a wide area and collect far more data than could be returned at each command cycle. Autonomy requirements for these missions would therefore be *comparable to or greater than* those of surface vehicles, and autonomous data understanding could play a significant role to improve science return. Onboard analysis could compute science-relevant summary descriptions of Titan's terrain to draft summary maps, identify key frames for transmission to Earth, and possibly choose locations to deploy opportunistic sensors.

Image analysis strategies used in ground-based platforms apply equally well to aerial imagery. Recent studies demonstrate automatic image classification based on quantitative texture attributes that correlate with morphological features [25]. These tests demonstrate fully automatic image analyses that are fast enough for onboard use and whose categorizations mirror expert interpretations of the scene. Mission planning and scheduling techniques also transfer to the aerial domain, permitting resource-cognizant reactions to science data [20]. Scientists may wish to target isolated features, maximize coverage of areas of interest, or reserve time for opportunistic data collection. Onboard data understanding provides the flexibility to pursue any or several of these goals while ensuring that the most valuable observations are included in the next downlink to Earth.

Orbital Platforms Limited by Communication

Imagery from the Mars Reconnaissance Orbiter (MRO) mission, in the form of Hi-RISE and CRISM data, has demonstrated the groundbreaking power of high-bandwidth orbital products such as high-resolution and hyperspectral images. Studies of fine morphological details reveal key mineral signatures that are highly localized or confined to a narrow layer of the geologic record [3, 14, 33]. These data products can assist *in situ* missions by resolving terrain features to identify landing areas and navigation hazards, and eventually by corroborating science measurements from the surface. However, innovation would be required to bring these benefits to future missions because the incremental upgrades planned for the deep space network will not support commensurate data rates to the outer planets.

Onboard science data analysis offers a promising path to relieving this bottleneck. Automatic onboard classification can interpret hyperspectral data [38, 37, 4, 38, 31, 32] or prioritize key images to enable fast reconnaissance of planetary surfaces. It has already proven particularly valuable for terrestrial orbital imagery and hyperspectral imagery in particular [13].

Spacecraft equipped with change detection can follow up opportunistically for dynamic phenomena such as volcanism. The EO-1 sciencecraft has identified volcanic eruptions and triggered followup observations without direct human intervention [13]. Algorithms for onboard detection of volcanism have also been demonstrated for Io and Enceladus images [2]. Many pushbroom imagers such as THEMIS, CRISM, or the IR imager considered for a potential Europa mission normally operate in a binned reduced-resolution mode due to bandwidth limits. Onboard analysis of data from pushbroom cameras can opportunistically apply full-resolution targeting to detected changes, areas of interest or compositional anomalies [39].

It is worth noting that onboard detection permits simultaneous, coordinated responses by multiple spacecraft for multimodal observations of transient phenomena. Earth observing assets have already been networked in this way, with observations by wide coverage assets that trigger followup observations by other assets with higher resolution or complementary modality [13]. As more assets are available for space science, enabling these sorts of synergistic observations or more pre-planned simultaneous observations will become of greater importance.

Recommendations

We close with recommendations for technology development and mission planning. It bears repeating that many of the technologies described above were developed under NASA programs that are no longer solicited. Building on the successes of initial efforts will require a greater resource commitment to develop new technologies and cultivate a pool of technologist talent in the area. In particular, <u>growing funds for AISRP and ASTEP programs would sustain these recent advances.</u>

It is equally important to recognize onboard data analysis in early mission planning. To date the infusion of onboard data analysis has occurred through extended missions. <u>We advocate planning explicitly for onboard science in advance and allocating resources to integrate these techniques into primary missions</u>. Onboard analysis could yield far greater benefits if the capability informs early instrument selection and software design decisions.

Automatic <u>onboard data understanding can improve the science return of long range (over-the-horizon) traverses.</u> The remote "field geologist" that surveys kilometers or tens of kilometers over the course of a mission can address significant science questions, and onboard data understanding can alleviate bandwidth constraints to make these operational modes feasible for outer-planets missions. Investments at the margin in the form of long-duration power, durable platforms, and long-lifespan instruments can enable wholly new survey-style investigations and yield profound improvements in science return.

Additionally, we emphasize that <u>bandwidth constraints need not preclude hyperspectral or high-resolution instruments</u>. NASA's current plans for the Deep Space Network have charted a conservative upgrade path. Onboard data understanding and spacecraft autonomy can reduce the reliance on a constant high-volume link to Earth. The popularity of the MER panoramas underscores high-resolution imagery's potential to engage public participation and create a sense of virtual presence. Autonomy can help meet these rising expectations in the future.

Finally, where margins permit, <u>expanded CPU capability and especially mass memory can enhance science return through application of these techniques.</u> Mars experience has shown that the software can be improved as the mission proceeds. While effective in the case of MER and EO-1, upgrades must overcome programmatic and institutional obstacles since they fit within existing flight software, computing resources and operations protocols. In the future we can catalyze adoption of onboard analysis with auxiliary computing resources and software design considerations. Large onboard memory caches can store data for later analysis at little cost in mass or power. These resources can benefit missions throughout the spacecraft lifespan as algorithms continue to improve.

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