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Cloud Filtering and Novelty Detection using Onboard Machine Learning for the EO-1 Spacecraft

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Abstract

We deployed three new data analysis algorithms onboard the Earth Observing 1 (EO-1) spacecraft and evaluated their performance over a five-month period. The algorithms include two cloud detectors and an unsupervised novelty detector. Together they provide the first demonstration of ensemble, Bayesian, and novelty detection methods onboard EO-1. Onboard performance on a diverse collection of targets was similar to or better than that observed in ground testing. These algorithms can be used to benefit future missions by aiding onboard decisions about data prioritization to optimize the use of limited downlink as well as potentially to enable autonomous response actions.

Introduction

The ability of modern remote sensing instruments to collect data often exceeds the bandwidth available for spacecraft to downlink the data to Earth. The communications link therefore becomes a "science bottleneck" in that it dictates how much information can be received. Traditional mission operations tailor their plans for data acquisition to the expected data volume available; in many cases this means a severe reduction in scope, resolution, or coverage.

Recent advances in spacecraft autonomy enable a more powerful and productive approach in which instruments collect more data than can be transmitted and employ onboard data analysis algorithms to identify valuable content within the data and prioritize it accordingly. This approach alleviates the bottleneck imposed by limited bandwidth and opens up the possibility of capturing rare phenomena whose occurrence cannot be predicted in advance.

The Earth Observing 1 (EO-1) spacecraft, in operation since 2000, has served as a pathfinder for onboard spacecraft autonomy. EO-1's primary science instrument is Hyperion, an imaging spectrometer that collects data at high spectral and spatial resolution. Over the years, a series of software upgrades have progressively increased EO-1's ability to analyze Hyperion data as it is collected to detect events of interest such as floods (Chien et al. 2013a) or volcanic eruptions (Davies et al. 2013). These detections can be used to prioritize data for downlink, add follow-up observations on the next overflight, or to alert other spacecraft that can collect their own observations.

Our goal is to use state of the art machine learning methods to enable onboard (in situ) spacecraft data analysis and optimize the use of limited downlink. This paper reports on the deployment of three new onboard data analysis modules for the EO-1 spacecraft. They employ machine learning to achieve cloud classification/filtering and novelty detection. In addition, these methods must operate successfully in a very constrained onboard operating environment (limited CPU, limited memory, and limited runtime) while minimizing risk and impact to the spacecraft as a whole.

Related Work

Previous work in onboard spacecraft autonomy includes methods that seek to (1) reduce (or make the best use of) data volume or (2) detect and respond to events of interest.

A reduction in data volume enables the collection of more data than can be transmitted. Autonomous data analysis methods complement standard data compression methods by applying mission-specific criteria to assess the scientific content of the data and prioritize it accordingly. For example, the Mars Exploration Rovers used a system called Watch to collect images for hours and only downlink those that contained active dust devils (Chien et al. 2008). The Intelligent Payload EXperiment (IPEX) CubeSat employed decision forests (Altinok et al. 2015) to assess image quality (e.g., to identify and exclude cloudy regions) prior to downlink. We also developed (but did not fly) onboard methods for summary product generation (thermal anomaly detection, polar cap edge tracking, and aerosol opacity estimation) for the Mars Odyssey orbiter (Castano et al. 2007).

Spacecraft have also used onboard data analysis to inform decisions about follow-up actions. For example, the Mars Science Laboratory rover now selects its own rock targets and fires the ChemCam laser to collect compositional data (Estlin et al. 2014). In Earth orbit, Swift MIDEX detects gamma-ray bursts and automatically slews the spacecraft to point additional telescopes at the source (Barthelmy et al. 2005). Spacecraft can even collaborate without human intervention: it is possible to detect floods in MODIS data and send an alert to the EO-1 spacecraft to automatically collect its own observation of the same area (Chien et al. 2013a).

Onboard Data Analysis for EO-1

Software onboard the EO-1 spacecraft must operate under significant constraints in terms of CPU cycles and memory available. The Mongoose M5 processor runs at just 12 MHz (4 MIPS), and the available RAM is only 128 MB. In addition, no dynamic memory allocation is permitted, and because there is no FPU, floating point operations must be emulated and are therefore extremely expensive.

There are also limits on how much data can be accessed onboard. Although the Hyperion instrument collects data at 220 wavelength bands, onboard software is permitted access to only a small subset of the bands, and only for a sub-region of the full image, which is 256 pixels wide and of variable length (tailored to the desired observation; typically 1024 pixels) (Chien et al. 2013b).

EO-1 has a history of performing onboard science-based data analysis including thermal anomaly detection to identify volcanic eruptions (Davies et al. 2013), flood detection (Ip et al. 2006), a support vector machine (SVM) to classify cryosphere features (Castano et al. 2006), a different SVM trained to detect tiny traces of sulfur deposits on glaciers as a possible analog for biosignatures on Europa (Mandrake et al. 2012), and spectral unmixing to classify surface materials (Thompson et al. 2013).

Onboard Data Analysis Algorithms

We implemented three new data analysis algorithms for Hyperion that include the first ensemble method and the first Bayesian technique to be used onboard EO-1. The first two methods address the task of identifying cloudy regions within a Hyperion image. The last algorithm identifies locally anomalous regions within an image that may contain new discoveries or features of interest. Each algorithm was allowed to select three Hyperion bands for its use. In all cases, the observed radiance values were converted to reflectance prior to analysis.

Cloud Detection with a Random Decision Forest

Hyperion is generally used to observe features of interest on the surface of the Earth. Intervening clouds obscure the surface and render the corresponding spectral information unusable. Detecting cloudy pixels onboard the spacecraft enables intelligent data prioritization or filtering to make the best use of limited downlink.

We trained a semantic texton forest (STF) to classify Hyperion pixels as "clear" or "cloudy." The STF is a random decision forest (RDF) that is tailored for analyzing images (Shotton, Johnson, and Cipolla 2008). It uses a diverse ensemble of decision trees, each trained on a slightly different subset of the data. Each tree classifies a given pixel by applying a series of tests to the pixel and its local neighborhood (window). The training process identifies the best test to use at each node in each tree to achieve the highest performance.

We started with an RDF implementation called TextureCam (Thompson et al. 2012; Wagstaff et al. 2013) that we previously demonstrated onboard the Earth-orbiting IPEX CubeSat (Altinok et al. 2015; Chien et al. 2016). We developed a static implementation of the TextureCam C++ code with serialized data structures that did not require any dynamic memory allocation. Once the RDF classification code was uploaded to EO-1, new decision forests could be trained on the ground and sent up to provide new capabilities without any code modifications.

The RDF cloud classifier was trained on four hand-labeled images in which individual pixels were marked "clear", "cloudy", or left unlabeled. These images were chosen to contain a variety of cumulus and stratus clouds, over land and water. They included observations from 2013 to 2016. The RDF used Hyperion bands at 478, 529, and 651 nm, which roughly correspond to blue, green, and red wavelengths. We performed a 4-fold image-based cross-validation study to select the best parameters for the RDF. The best-performing model, given the memory available, was a forest with two trees, nine nodes per tree, and an analysis window size of 5 x 5 pixels. This model achieved an average held-out precision of 94.9% and recall of 77.2%. Since cloud classifications could potentially be used to reduce priority or omit data segments, precision is much more important than recall.

Cloud Detection with Bayesian Thresholding

Our second algorithm (BT) also classifies pixels as "clear" or "cloudy" using a different approach to the problem. Bayesian thresholding exploits the natural division between dark surface materials and bright cloudy regions at particular wavelengths. The BT algorithm analyzes labeled training data and identifies the optimal thresholds for each band to separate the classes of interest. While the RDF method examines a window of values around the pixel to be classified, BT classifies each pixel independently. This approach was previously employed to analyze data collected by the AVIRIS-C airborne sensor (Thompson et al. 2014). For EO-1, BT used Hyperion bands at 447, 1245, and 1658 nm to span the range from blue to short-wave infrared. The BT algorithm was ported from Matlab to C++, and the output data format was updated to provide a cloud mask output.

The BT model was trained using an updated set of 11 hand-labeled images from late 2016 and early 2017, just prior to deployment of the classifier. The model achieved an average held-out precision of 90.6% and recall of 65.8%. For flight, we increased the selected thresholds slightly to further emphasize precision.

Salience-based Novelty Detection

Supervised machine learning methods are useful when we know in advance which features are of interest. However, when exploring a new environment, it is equally important to be able to detect the unexpected. We previously developed an algorithm that computes the *salience* of image content, so that highly unusual or anomalous regions can be assigned a high priority for downlink (Wagstaff et al. 2012). We implemented it for use on IPEX between 2013 and 2015; to our knowledge, this was the first use of salience estimation onboard a spacecraft. On IPEX, the salience algorithm de-

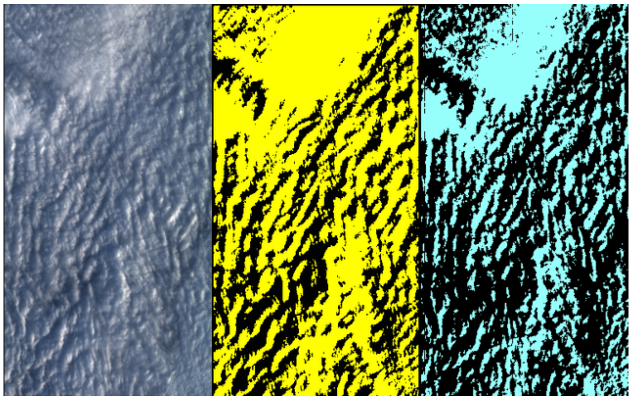

Figure 1: EO-1 onboard cloud detection for a scene in Michigan: RGB (left), RDF clouds (middle), and BT clouds (right).

tected several small features of interest such as small lakes in Tibet, despite no prior training (Chien et al. 2016).

Salience is an unsupervised algorithm that assigns a score to each pixel that captures how anomalous it is within its local context. The salience S of pixel p is computed with respect to the histogram P_w of intensity values in the surrounding window w:

$$S(p, w) = \frac{1}{M} \sum_i |p - i| P_w(i) \tag{1}$$

where M is a normalization factor that is the maximum salience possible given the window histogram and size: $M = N(N-1)\sum_i P_w(i)$.

We adapted the salience algorithm for use on EO-1 in two ways. First, we improved efficiency by computing the histogram incrementally as the analysis window slides across the image, instead of computing it from scratch for each window. Second, we extended salience to operate on multi-wavelength observations by computing salience independently for each band and then reporting the maximum salience across all bands. We used the same RGB bands as the RDF classifier and a window size of 31, which is sensitive to medium-scale features.

Results

Onboard operation of the RDF, BT, and salience algorithms occurred from November 2016 through March 2017. We chose a range of targets for testing the algorithms, including desert, mountain, lake, and urban environments.

The RDF cloud classifier was run a total of 22 times. Three results were lost due to data gaps or corruption. In the remaining 19 images, clouds were correctly detected in six of eight cloudy scenes. The two missed scenes had very thin clouds or low illumination. In two other scenes, clouds were falsely detected due to bright surface deposits or snow.

The BT cloud classifier was run only seven times due to its later deployment. It correctly detected clouds in two of three cloudy scenes; the missed scene's clouds were rejected as too thin. There were no false detections. Figure 1 shows results for both classifiers on the same cloudy scene. They largely agree, although the BT classifier is more conservative, as designed.

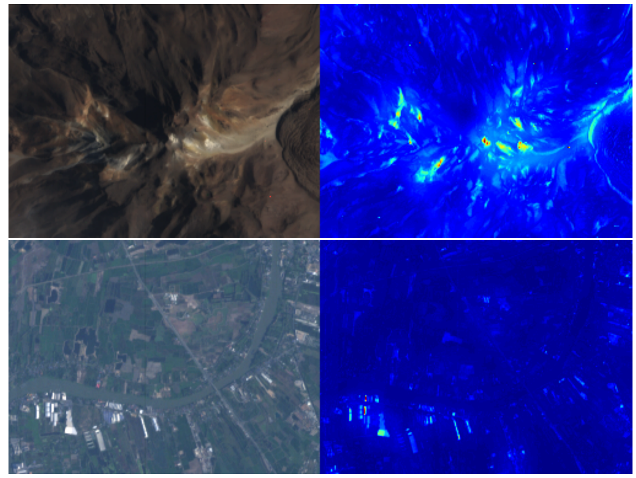

Figure 2: EO-1 onboard novelty detection for a volcano in Chile (top) and buildings in Thailand (bottom): RGB (left) and salience heat map (right).

The salience algorithm also generated a total of 19 results. Regions with high salience scores were diverse, including mountains, channels, streambeds, buildings, and cloud edges (see Figure 2).

The BT algorithm was the fastest to run; it required 18 minutes to process a 256 x 1024 3-band Hyperion image. The RDF time was variable because the decision forest follows different paths depending on the data content; the average was 52 minutes. The salience algorithm had the longest average runtime (160 minutes). In the future we would recommend using the single-band version of the algorithm, which would require only 1/3 of the observed runtime ($\sim$53 minutes). We did not observe significant differences when using one versus three bands.

Conclusions

The upload of three new data analysis algorithms to the EO-1 spacecraft provides a critical step in their maturation and potential use by future missions. Detecting and screening clouds can yield major benefits for Earth-observing instruments by reducing data volume. When data analysis is used to inform decisions about data prioritization and potentially deletion, the results must be reliable and conservative. Precision is generally more important than recall; it is better to mistakenly preserve a cloud than to mistakenly omit good data from the downlink.

While we can anticipate the need to classify some features such as clouds or floods or volcanic eruptions, there will always be a need for the ability to also detect the unknown. This is particularly vital for missions to more remote and less explored destinations, such as comets, ocean worlds, and distant moons. A complete onboard analysis system will need to integrate the detections and decisions of multiple analysis modules to inform final decisions about data prioritization and, potentially, active responses.

Future spacecraft will have progressively more powerful flight computers. The Mars rovers have exceeded EO-1's 12 MHz by an order of magnitude, and we expect this trend to continue. Greater computing resources open up the possibility of using larger, more complex and accurate models.

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