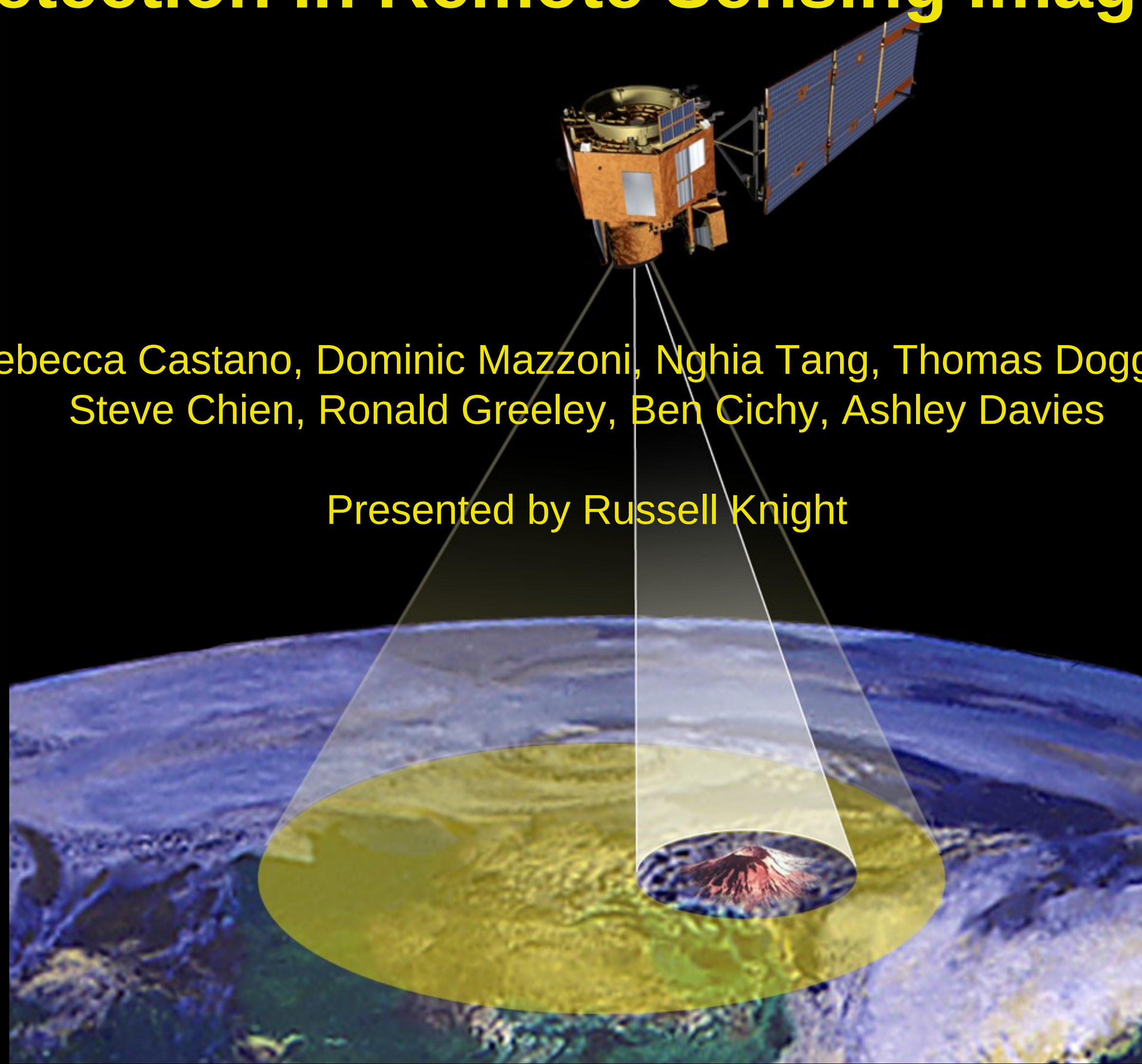
Learning Classifiers for Science Event Detection in Remote Sensing Imagery



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Presented by Russell Knight

Outline

- Introduction
- ASE/EO-1 Spacecraft
- Classifiers
- Testing and Experimental Results
- Future Applications

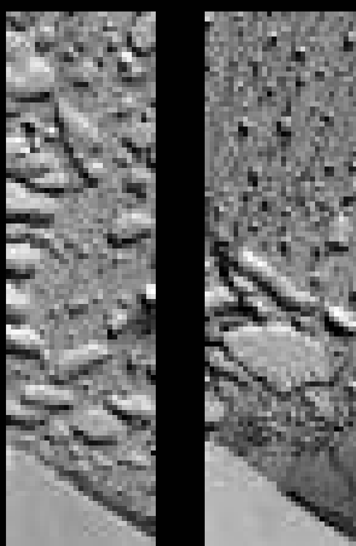
Onboard Science Data Analysis and Event Detection

Purpose

To increase science return by determining high priority science data for downlink and identifying dynamic science events

Example criteria for determining important science data

Change Detection



Sea ice breakup

Feature Detection

Volcanic eruption

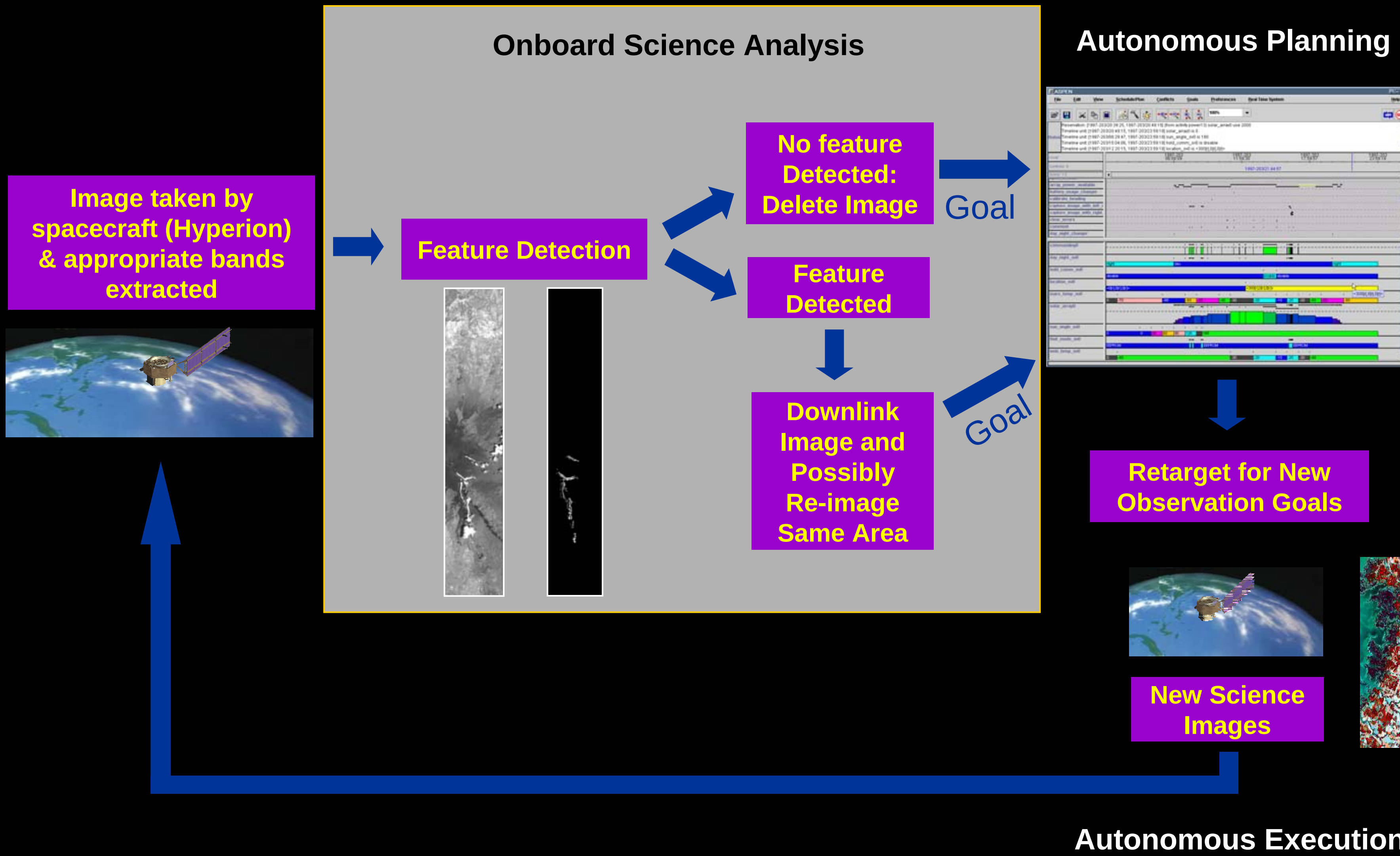
Data Quality Control

Cloudy

Cloudy

Clear

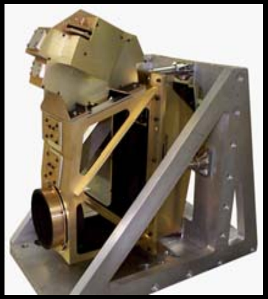
Autonomous Sciencecraft Experiment (ASE)



Technology Carrier: EO-1 Mission

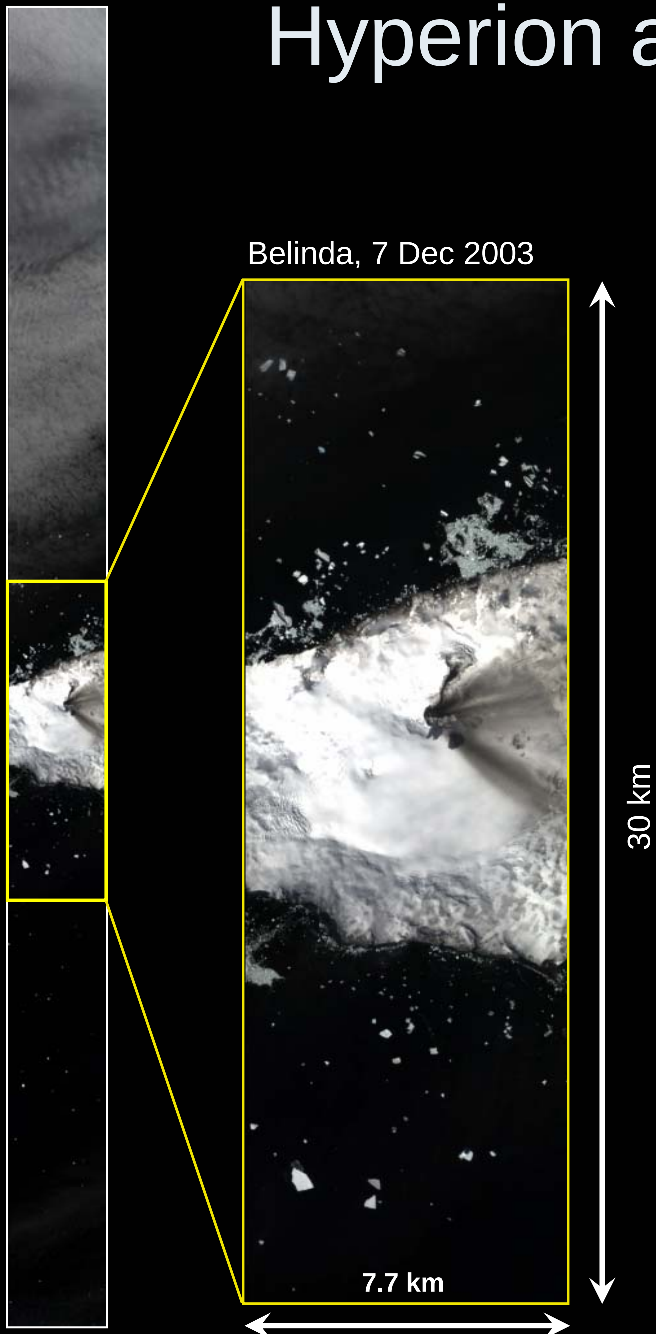
- Autonomous Sciencecraft Experiment (ASE)
  - Part of New Millennium ST6 Project
  - Subsystem demonstration
  - Funded to flight demonstrate autonomy software technology for future mission adoption
  - Uses Hyperion instrument (hyper-spectral imager)

- CDS: Two Mongoose V CPU's
  - Mongoose V @ 8 MIPS and 256 MB RAM
  - Flight control software on CDH CPU
  - Autonomy software on data recorder CPU



Hyperion

Hyperion and Science Classifiers



- Hyperion instrument
  - Hyperion is the EO-1 hyper spectral imaging spectrometer
  - 220 bands from 0.4 to 2.5 μm
  - 30 m/pixel spatial resolution
- Classifiers
  - Classifiers use up to 12 bands
  - 7.7 km x ~30 km area
  - Onboard classifiers use partially calibrated data (using dark calibration image)
  - Cryosphere classifier identifies pixels as land, water, ice, snow, cloud or unclassified

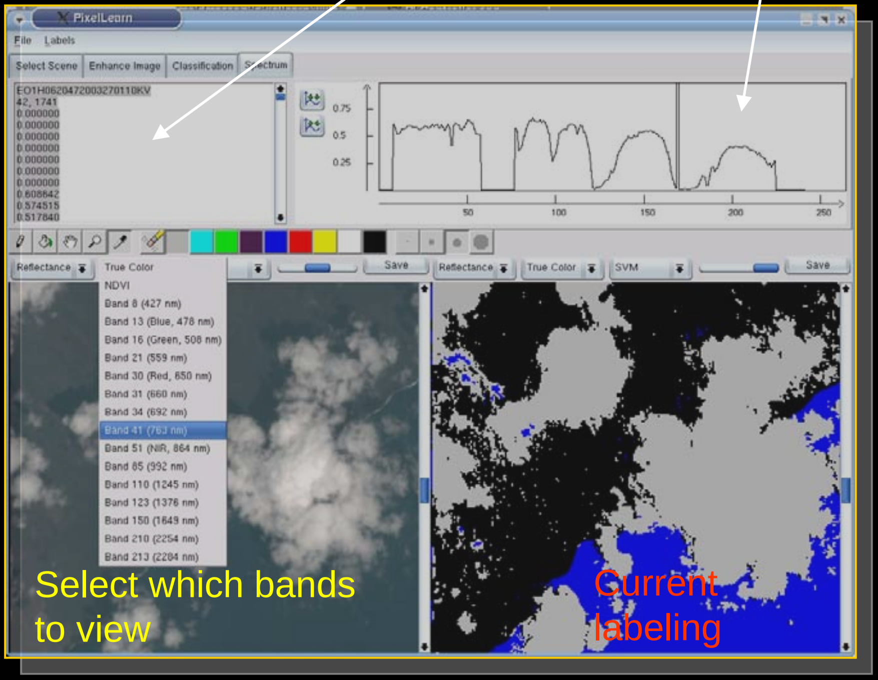
PixelLearn Training and Testing Tool

Issues

- Hand labelings of scenes are necessary to compare against in order to assess the performance of all classifiers, both expert derived and machine learning based
- Hand labels are necessary for training machine learning based classifiers
- Labeling data can be tedious and time consuming

Features

View all spectral values for a selected pixel



PixelLearn Innovations

- After a few representative areas are quickly marked by an expert, a classifier is *trained and run* on the scene in *real time*
- The expert then only has to update areas which were classified incorrectly, i.e. challenging pixels
- Process can be iterated

Expert Derived Classifier

- Classifier derived empirically using 175 spectra selected from a number of different images
- Band ratios and thresholds were selected to best distinguish the pixels selected
- The set of training images were then classified and regions incorrectly classified were identified visually
- The spectra were inspected and a new decision layer was added to the classifier to correct significant misclassifications
- This procedure was iterated until a sufficiently high accuracy was achieved.
- Final version employs a sequence of 20 steps

Excerpt of expert derived classifier

...

$$\frac{r21 - r150}{r21 + r150} < 0.176$$

Then classify pixel as cloud

Else if $\frac{r21}{r31} < 0.91$

Then classify pixel as cloud

Else if $\frac{r21 - r150}{r21 + r150} > 0.56$ and $\frac{r21}{r31} < 1.11$

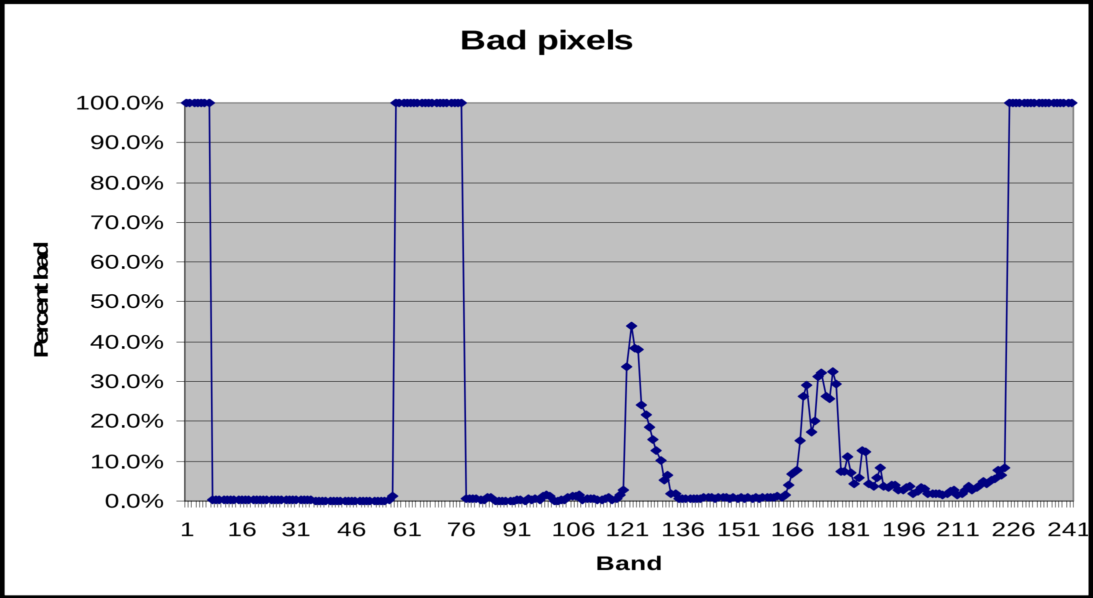
If $\frac{r21}{r31} < 1.0$

Then classify pixel as snow

R21 indicates the DM (radiance) value of band 21 converted to a reflectance value

Development of Best Ratio Classifier

- Baseline automated classifier
- Approach
  - Eliminate all bands with 1% or greater noise pixels
    - 150 bands remained
  - Identify optimal threshold for all possible ratios
    - 11175 ratios considered for each class
  - Determine best ratio and threshold for each class using one-vs.-all comparison (class vs. not class)



Best Ratio Classifier

- Evaluated ratios of
  - Reflectance
  - Radiance
  - Raw values
- Considered
  - Band ratios
  - Normalized difference
  - Single band thresholding

If $B_{16}^{refl} / B_{36}^{refl} > 1.42$

Pixel = Water

Elseif $B_{18}^{raw} / B_{44}^{raw} > 1.37$

Pixel = Land

Elseif $B_{37}^{rad} / B_{43}^{rad} > 1.14$

Pixel = Ice

Elseif $B_{188}^{raw} / B_{217}^{raw} > 1.33$

Pixel = Cloud

Elseif $B_{120}^{refl} / B_{140}^{refl} > 0.93$

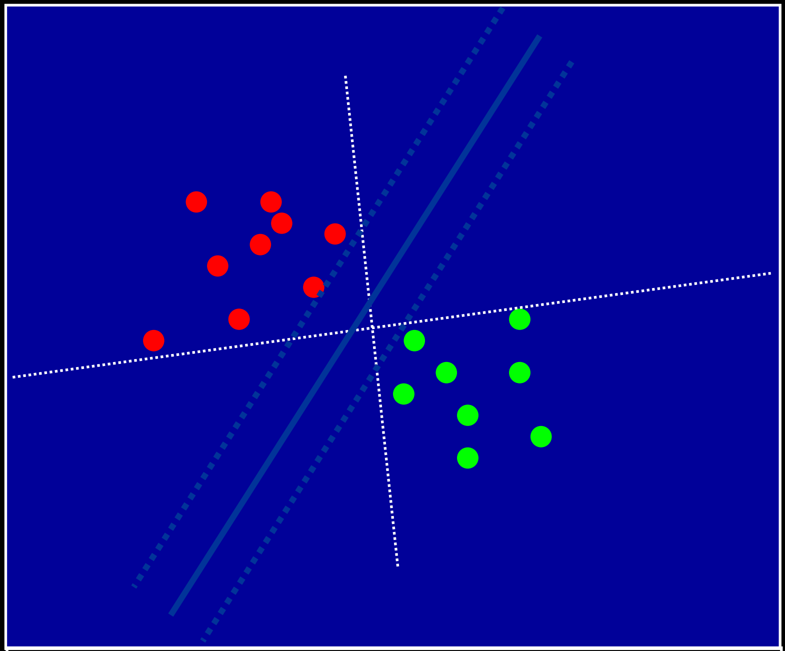
Pixel = Snow

Else Pixel = Unclassified

Decision Tree Classifier

- C4.5 Algorithm used to construct the classifier
- Candidate features
  - 11 bands (selected by expert)
  - 55 band ratios (ratios of all pairs of 11 bands)
  - Principle components of training data
    - Impractical for onboard use, but included to determine if increased accuracy would be possible using this method if more computational power were available.
  - A secondary classifier to distinguish between just two classes was used in cases where two classes were often confused
- Final classifier
  - Uses 11 bands plus a cloud vs. land secondary classifier
  - Both primary and secondary trees have a depth of 12

Support Vector Machines (SVM)



The turquoise lines represent the optimal hyperplane and its corresponding margin for these data. White lines are non-optimal hyperplanes.

- Creates classifier that separates two distinct classes
- Maps the data into a high dimensional space and finds a hyperplane that separates data from two classes
- The optimal hyperplane maximizes the margin (the distance between the hyperplane and nearest points from the two classes)
- Kernels used:
  - linear
  - Gaussian radial basis function (rbf)
  - normalized polynomial (npoly)

Support Vector Machine Classifier

- Characteristics of classifier
  - Linear classifier used to reduce computational cost
  - 11 bands (selected by expert)
- Benefits of SVM classifier
  - High accuracy (see results)
  - Minimal expert time required to develop classifier (in contrast to the manually developed classifier)
- Drawbacks of SVM classifier
  - All bands must have valid values (this is not true for the other three classifiers which may fall out, i.e. reach a decision before evaluating all 11 bands)

Experimental Results

50 images were used for testing

Class	Abundance in test set (%)
Cloud	17
Ice	2
Land	59
Snow	14
Water	8

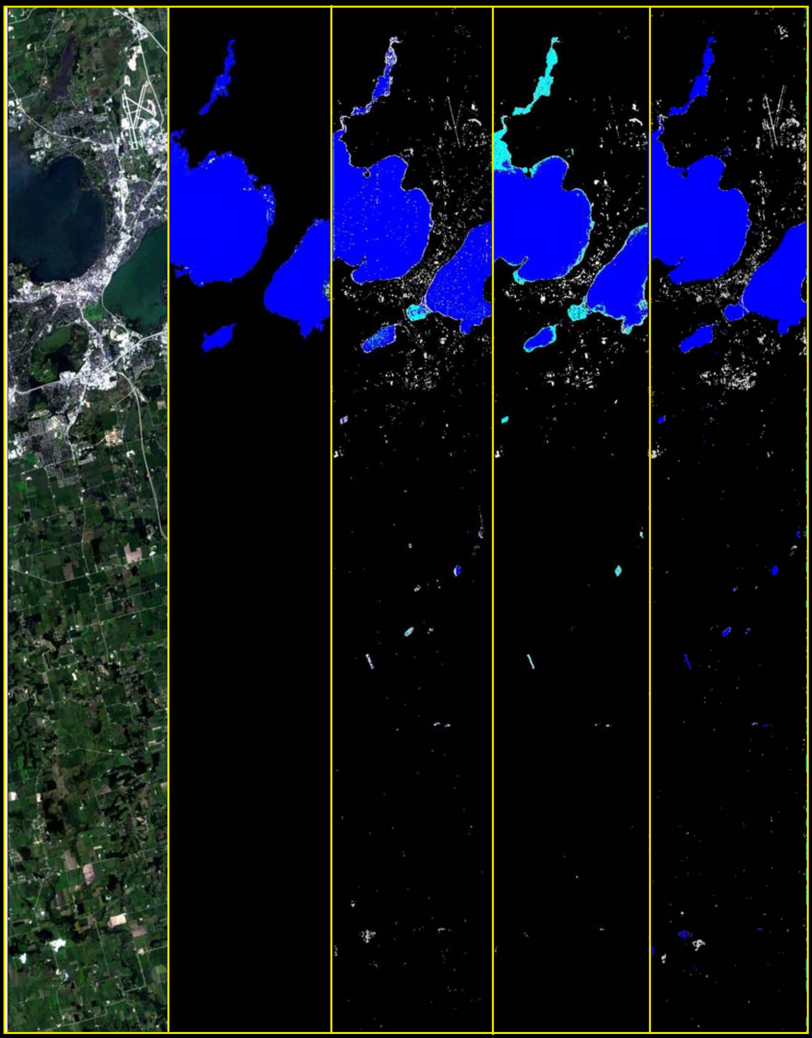
Key	
Cloud	
Ice	
Land	
Snow	
Water	

Overall Accuracy

	Expert Derived	Best Ratio*	Decision Tree	SVM
With Unclassified Class	82.9	76.6	80.9	81.3
Unclassified assigned to Water	83.0	76.7	80.9	83.8

* Slightly different test set

Lake Mendota, Wisconsin



Visible Image | Expert Labeled | Expert Derived | Best Ratio | SVM

Performance Assessment

Precision

$$P = \frac{TP}{TP + FP} * (100)$$

	Expert Derived	Best Ratio*	Decision Tree	SVM
Cloud	77.2	77.4	80.2	83.3
Ice	53.3	34.2	31.0	39.9
Land	93.7	93.0	92.5	95.3
Snow	71.4	76.5	72.5	78.5
Water	81.0	59.1	73.5	63.6

Recall

$$R = \frac{TP}{TP + FN} * \left(100\right)$$

	Expert Derived	Best Ratio*	Decision Tree	SVM
Cloud	55.1	77.4	57.2	65.7
Ice	49.7	34.2	62.4	47.8
Land	95.7	93.0	93.0	95.2
Snow	84.3	76.5	76.7	77.4
Water	91.0	59.1	91.2	66.1

* Slightly different test set

Onboard Classifier (SVM) Test


Visible image

12/01/2004
Image of South Georgia Island near Antarctica analyzed onboard EO-1 by the SVM classifier

Classification Results:

Snow	847
Water	254095
Ice	1148
Land	4725
Unclassified	0
Cloud	1329

Trigger Criteria:

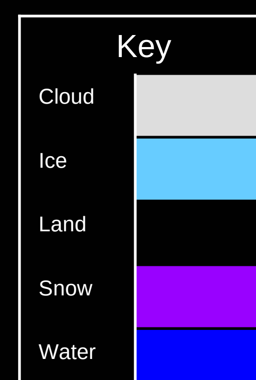
$$\frac{Cloud + Unclassified}{Total} < 60\%$$

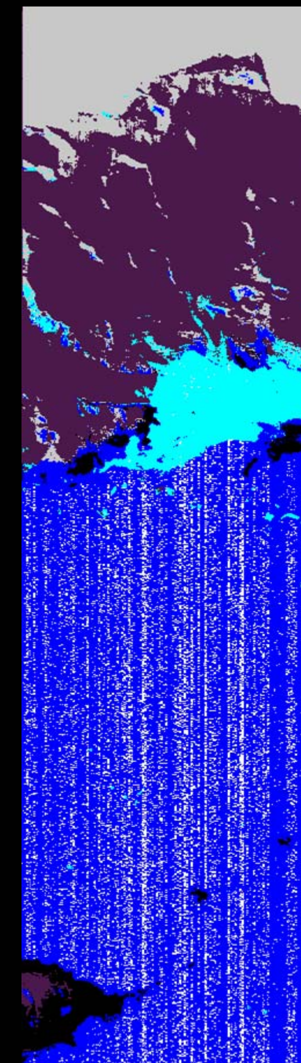
and

$$\frac{Snow + Ice}{Snow + Water + Ice} < 86\%$$

Correctly classified as open water; meets sea ice break-up criteria to trigger re-image of South Georgia Island on 12/03/04

Note: Re-image is desired to track the change occurring as the ice breaks up

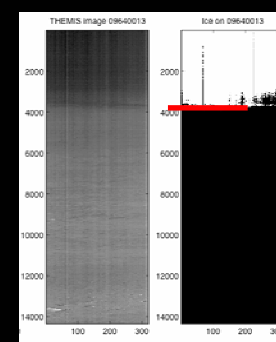



Classifier results

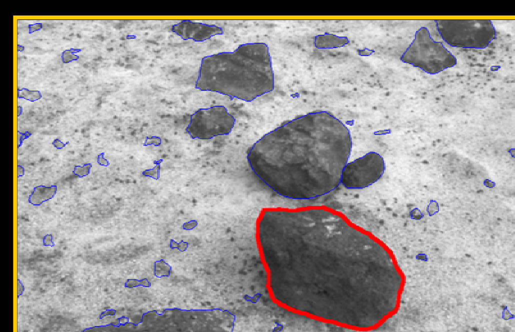
Feature Detection Infusion Targets

- MER - dust devil/cloud detection
- THEMIS – science event detection
- MSL - instrument target selection

Dust devil detection



Mars polar cap edge detection



Instrument target selection

Conclusions

- Onboard data analysis can
  - Enable returning the most important science data
  - Enable rapid response to short-lived science events
- Machine learning classifiers for onboard data analysis shows great potential for use in future deep space missions, where the round trip messaging times make the reaction to dynamic events difficult to impossible with the traditional ground-in-the-loop approach.
- Machine learning can achieve similar results to expert derived methods at considerable savings of expert time
- Techniques apply to a wide range of sensors and event types