# Autonomous On-board Near Earth Object Detection

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Detection, Tracking and Identification of Asteroids through On-board Image Analysis

Purnima Rajan
Graduate Student, Laboratory for Computational Sensing and Robotics
Johns Hopkins University

# Research Objectives & Results

## Objectives

- Develop asteroid detection, identification, and tracking algorithms that can be hosted on a spacecraft
- Implement the algorithms on the flight-like environment to demonstrate feasibility of on-board asteroid detection
- Apply machine learning techniques to minimize false positives

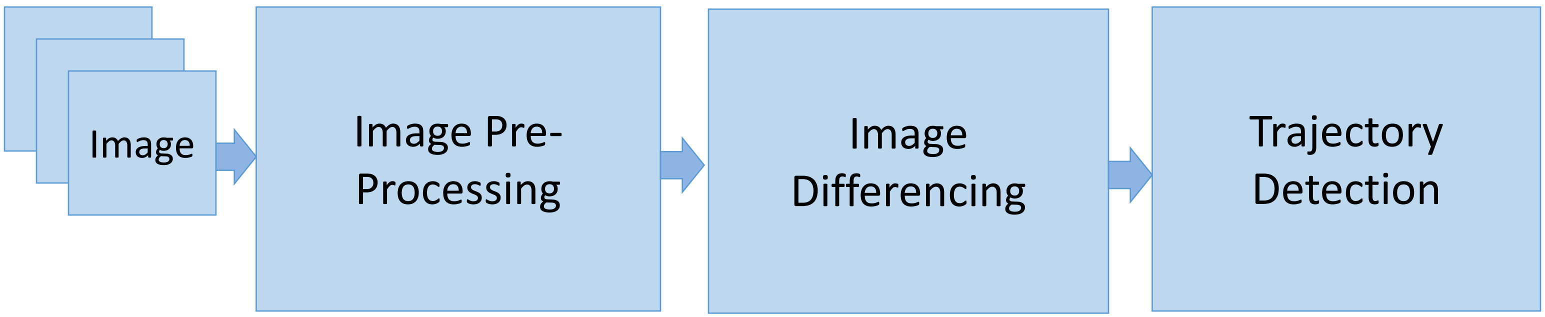
## Results

- Detection algorithm can fit on a MCP-750 (233 MHz)
- Developed a tool suite that enables instrument and spacecraft design trades

# Outline

- Algorithm Description
- Algorithm Performance and Analysis
- Ongoing / Future Work

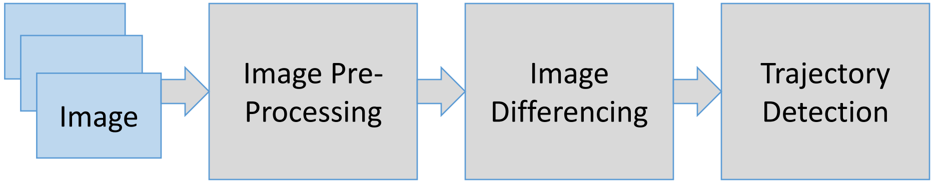
# Image Processing Pipeline

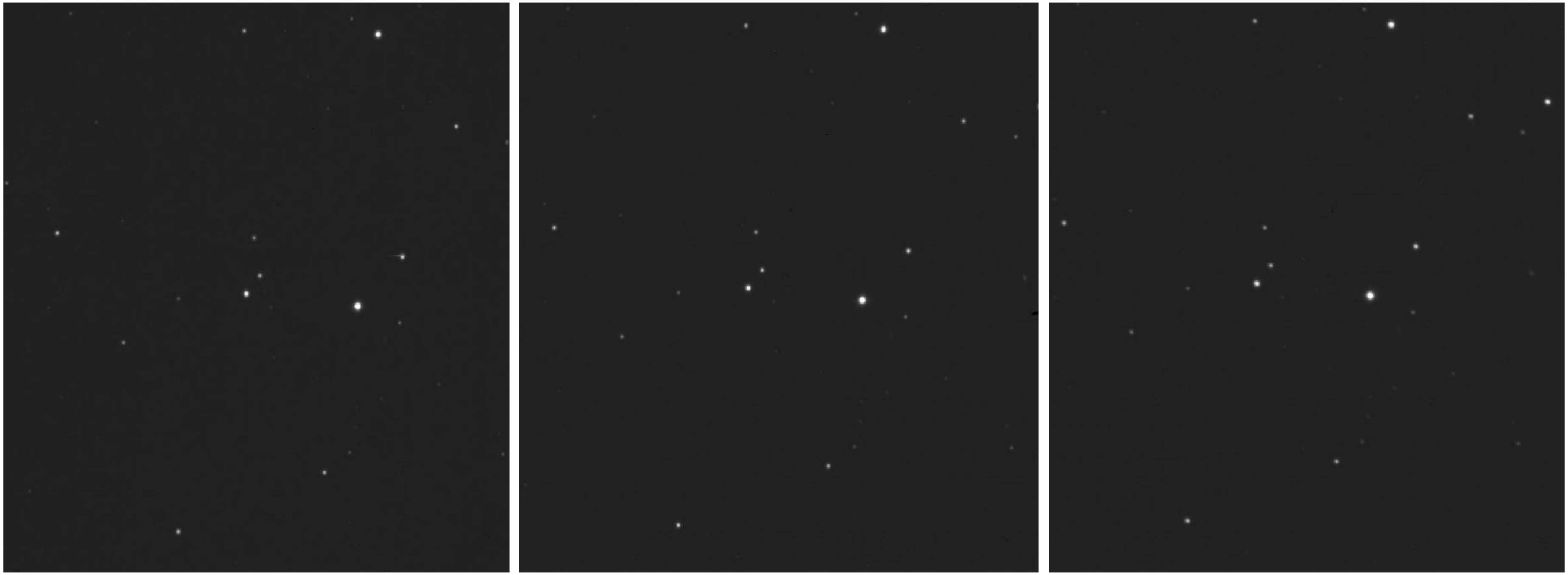



Assumptions:

- A sequence of 3 or more overlapping images is taken
- The SNR and imaging conditions are such that the asteroid is visible (even if faint)

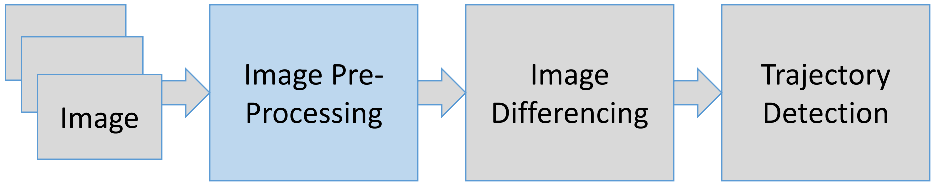
# Image Processing Pipeline
# Input Image Sequence



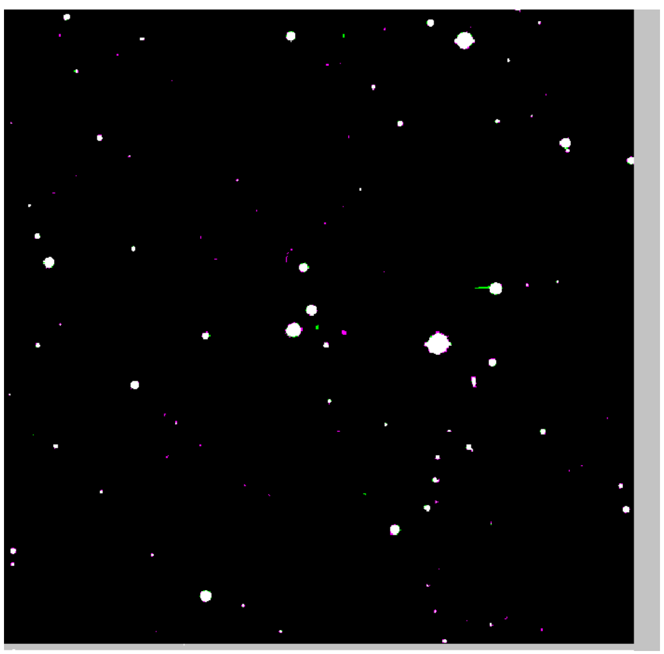



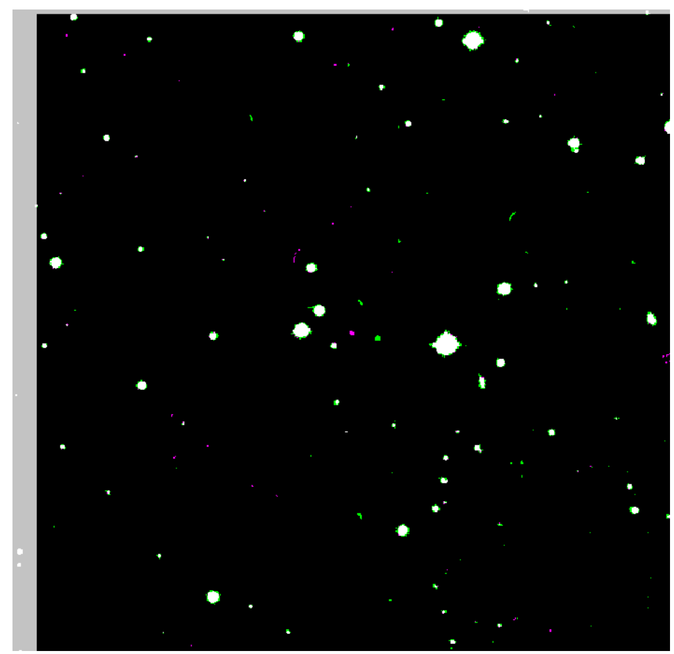
**2002 CY46 Triplet (FITS images)**
**Near Earth Asteroid Tracking(NEAT) system archive**

# Image Processing Pipeline

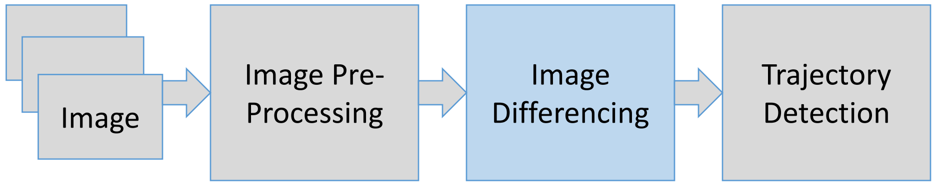



- Image Pre-Processing
  - Median filter
  - Dynamic thresholding at mean plus 1 SD brightness

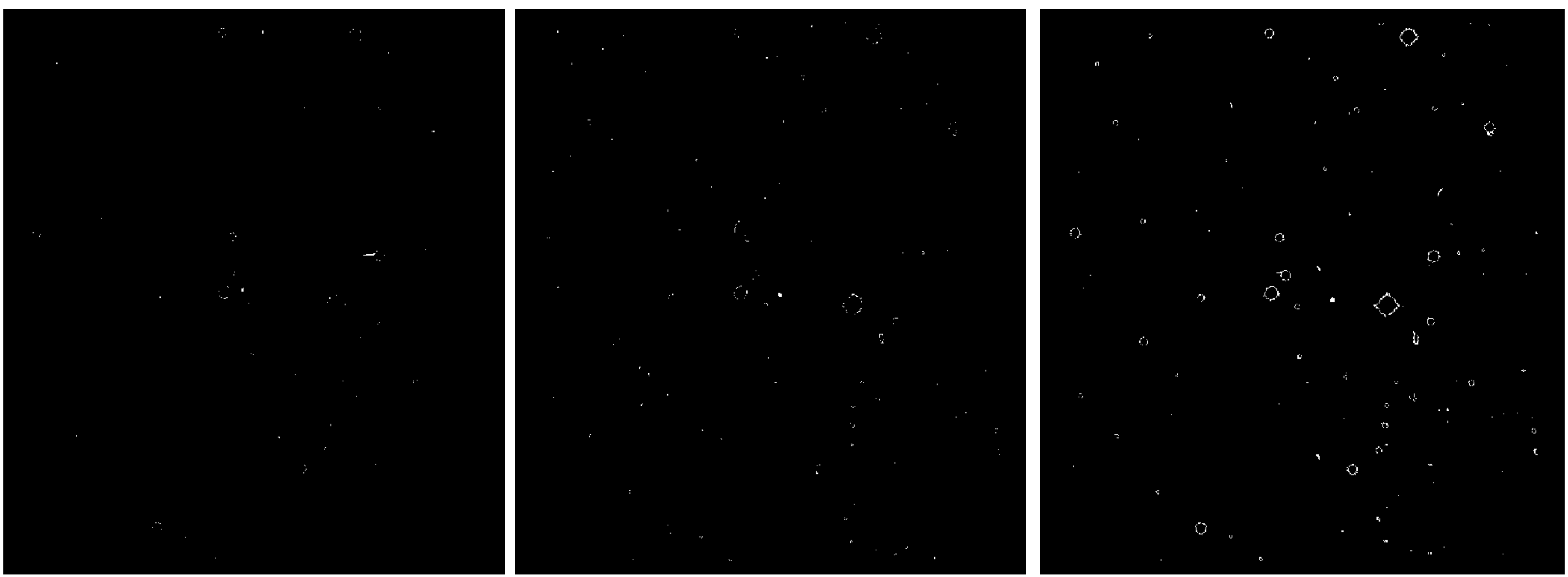




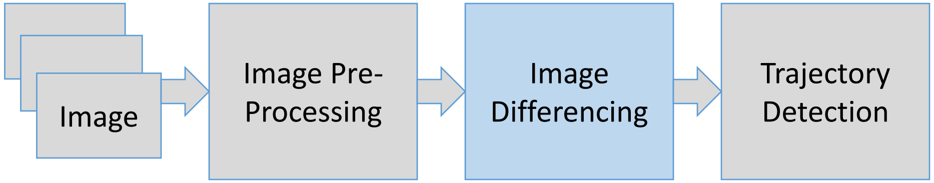
# Image Processing Pipeline



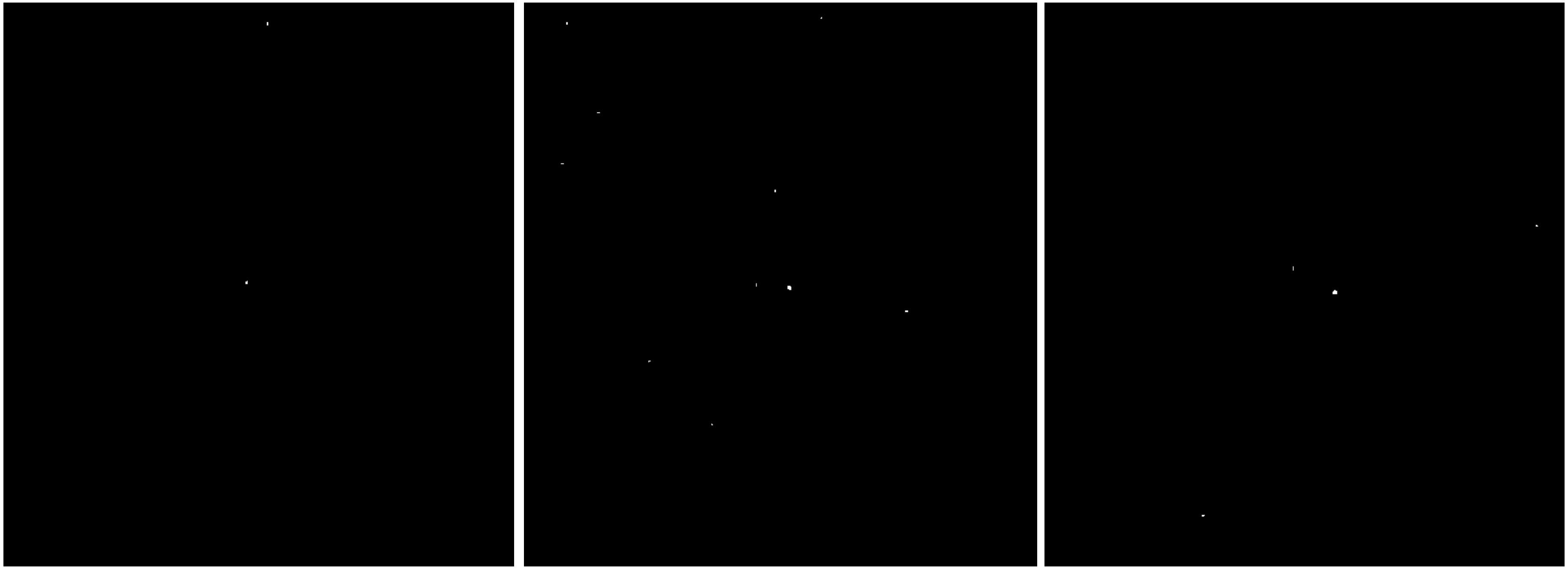

- Logical Differencing: $d_i = b_i \,\&\, {\sim}C$, where $C = (\sum_i b_i) \geq 2$



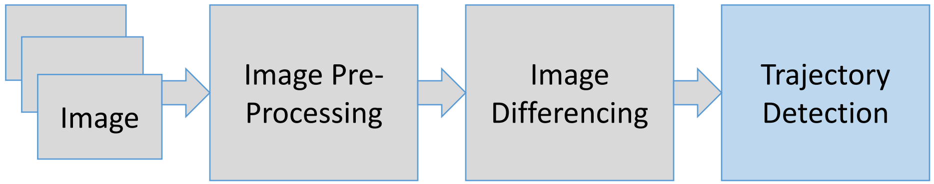
# Image Processing Pipeline




- Replace each connected component by its center of gravity
- Filter on size/shape

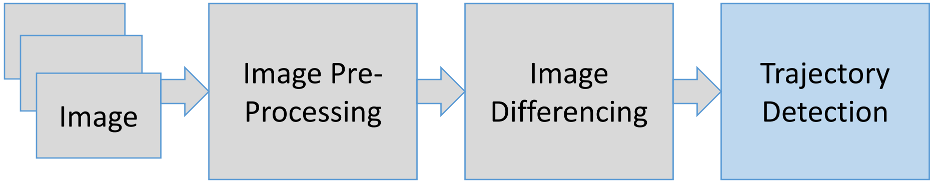


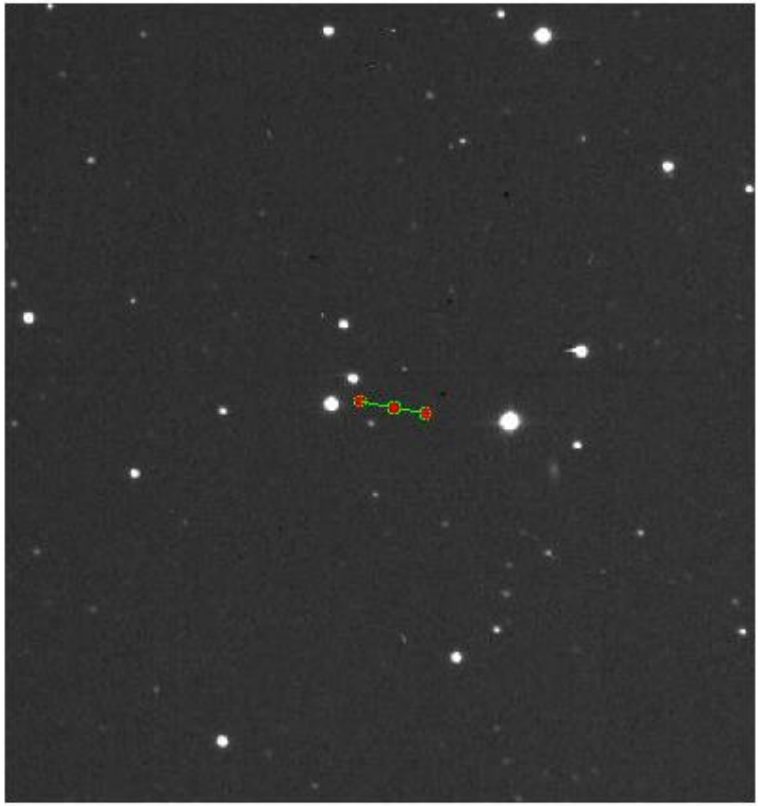
# Trajectory Detection




- For each ${}^{K}C_2$ pairs of images $I_k$, $I_j$
  - For each detection pair $(d_{k,n}, d_{j,m})$, $d_{k,n}$ in $I_k$ and $d_{j,m}$ in $I_j$
    - V=0
    - For each $I_s$, $s \neq k,j$
      - Find the point of intersection $d_s$ in $I_s$, $s \neq k,j$
    - If detection within 5x5 neighborhood of $d_s$
      - V=V+1
  - If V > Vmin
    - Record $(d_{k,n}, d_{j,m})$ as a detection

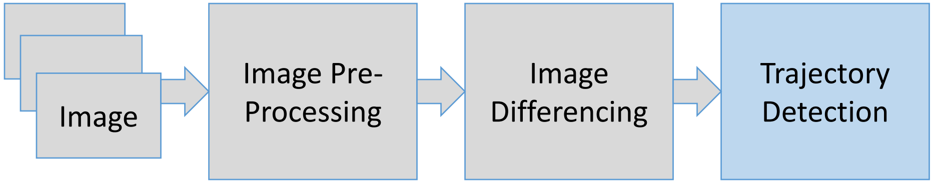
# Trajectory Detection

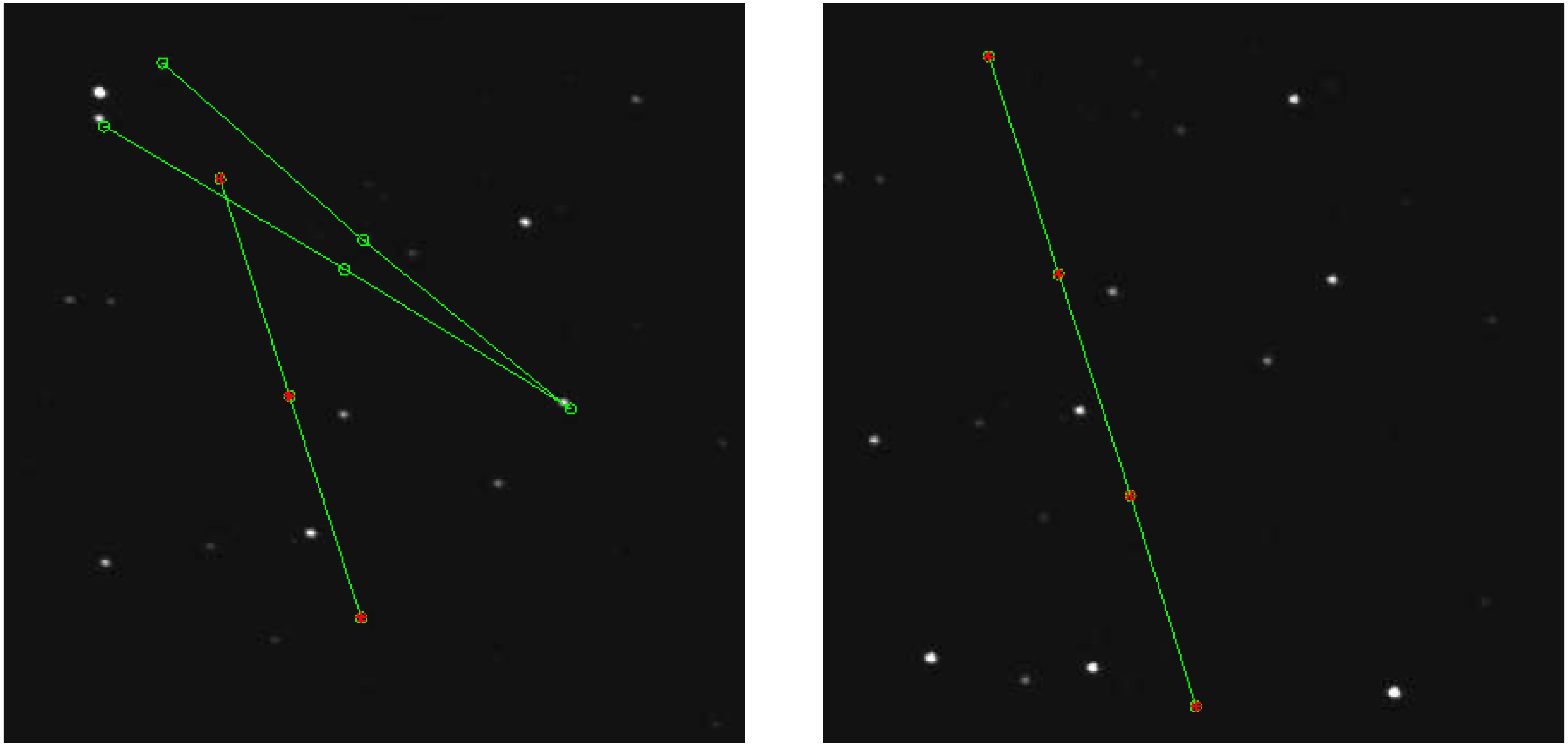


Trajectory Detection for superimposed CY46 Triplet.
Asteroid trajectory detected is shown in green. True location is in red.

# Trajectory Detection
# Triples vs. Quadruplets



Left: Trajectory Detection for the CSS Triplet. Right: Trajectory Detection for the CSS quadruplet. Asteroid trajectory detected is shown in green. True location is in red.

# Algorithm Validation Approach

| Program | Waveband | Time series | Available data sets | Ground truth availability | Available 'raw' (level 1A) data |
|---|---|---|---|---|---|
| Near Earth Asteroid Tracking(NEAT) | 400-900 nm (visible) | 20 minutes | 13 triplets | yes | None |
| Catalina Sky Survey(CSS) | visible | ~10 mins | 2 quadruplets | yes | None |
| Pan-STARRS | .5-.8 microns (visible) | ~30 mins | Pairs only | no | None |
| NEOWISE | 3-4 microns | ~2 hrs | ~30 images per sequence | no | None |

- Real imagery that met our assumptions was very limited
  - Majority were ground-based telescopes (NEAT, CSS, Pan-STARRS)
  - Difficult to obtain NEOWISE (space-based) imagery that met our assumptions
  - None in optimal waveband (6-10 micron)
- Employed simulated imagery to provide statistical analysis

# Outline

- Algorithm Description
- Image Simulation
- Algorithm Performance and Analysis
- Recommendations
- Ongoing / Future Work

# Performance Analysis

- Extensive testing as a function of telescope parameters and asteroid characteristics
- Chose 0.5m aperture as best tradeoff of detection vs. size
- ROC curves
  - True Positives per sequence is the mean number of true asteroid detections in each image in the sequence.
  - False Positives per sequence is the mean number of false detections in each image in the sequence.

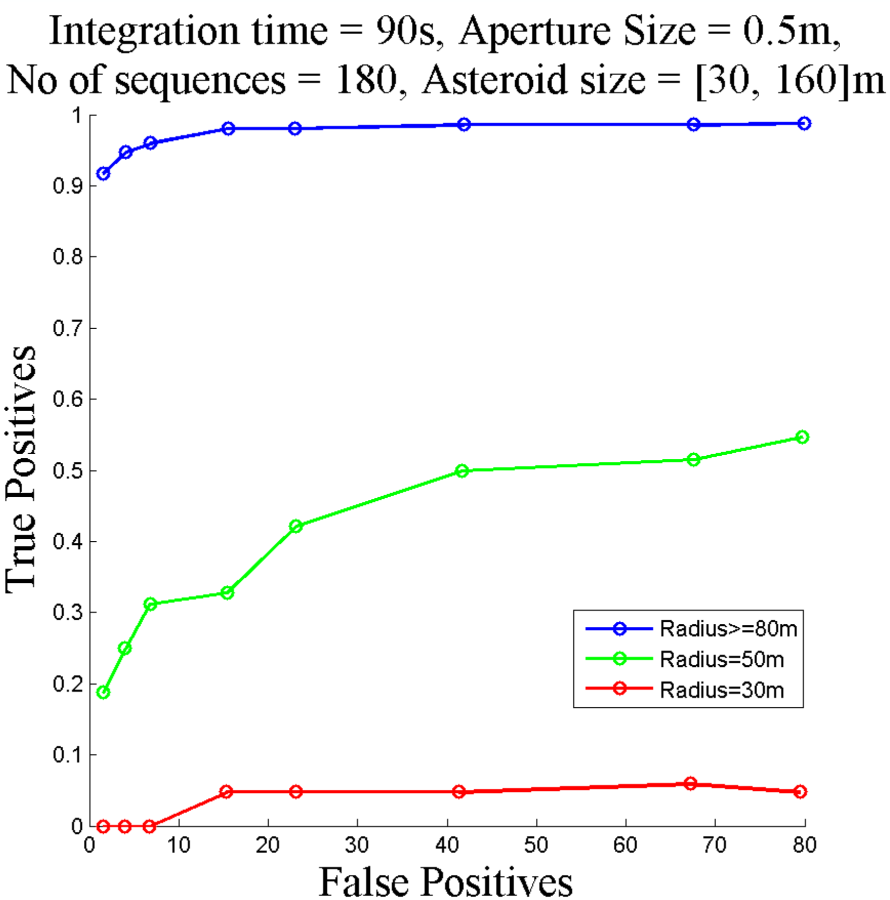
# Performance Analysis

- Stratified ROC curves based on asteroid size, distance and SNR

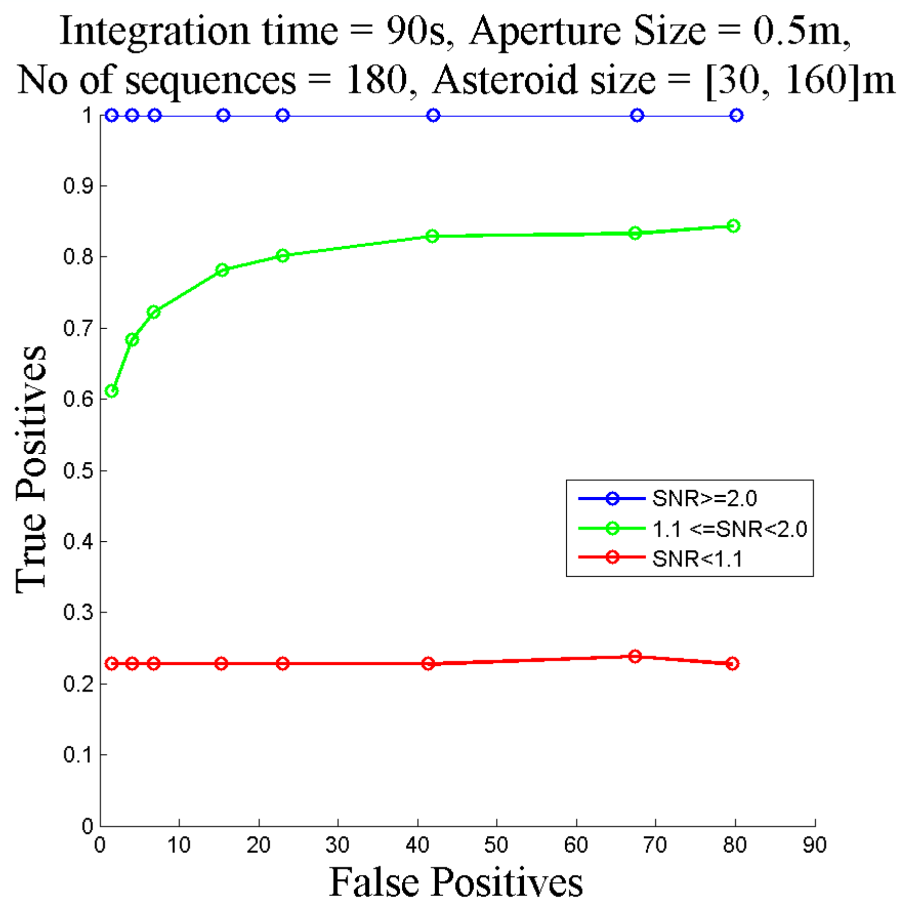
- SNR computed as follows
  - Signal
    - Choose a 3x3 window around the asteroid ground truth.
    - Find the maximum pixel value within this window for each image in the sequence
    - Take the median of these maximum values

  - Noise
    - Remove the upper 10% of the grey levels in each image
    - Compute the mean of the remaining pixels in each image
    - Take the median of these trimmed means

# ROC as a Function of Size and SNR



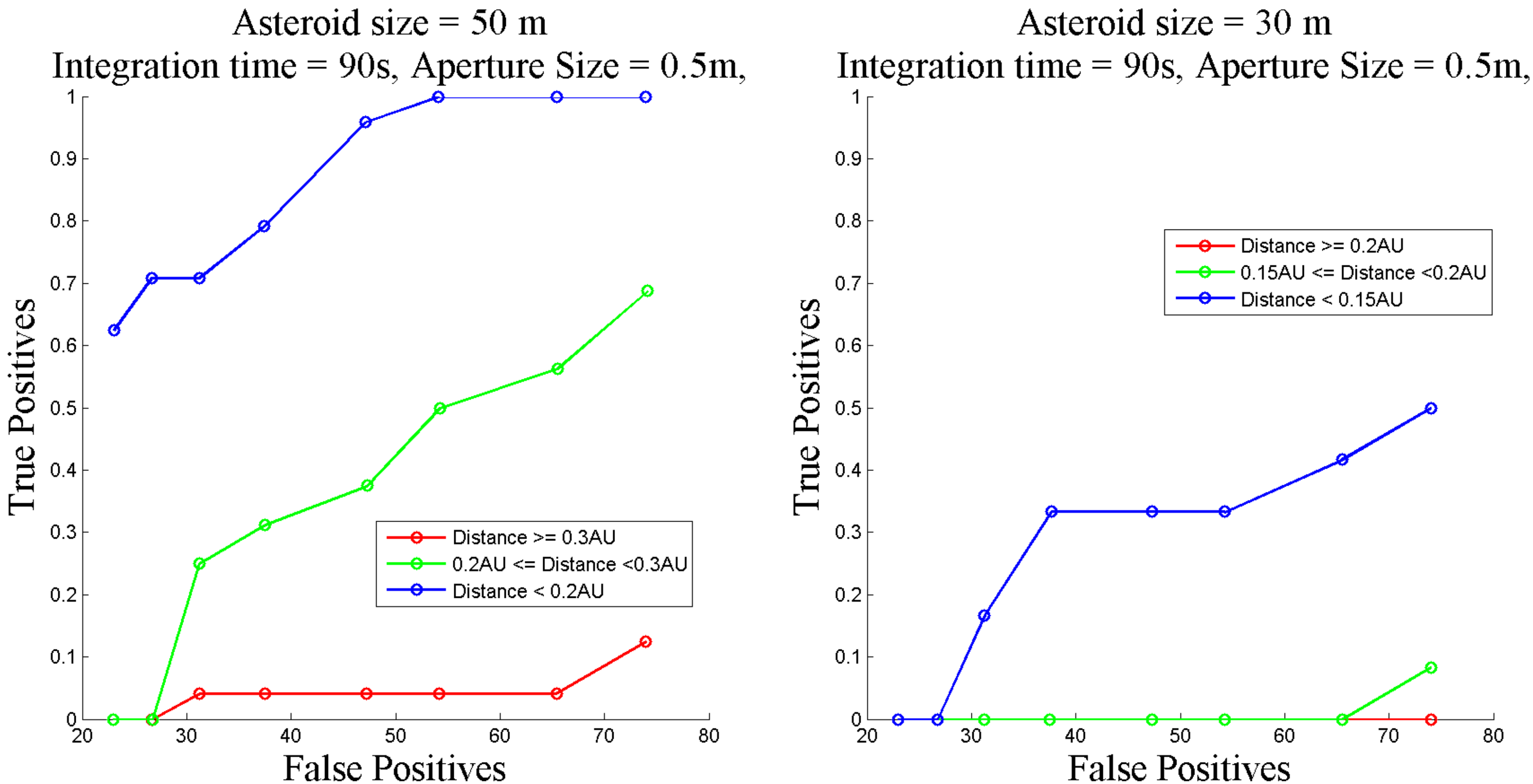

**Size**




**SNR**

4 images per sequence, line threshold = 3

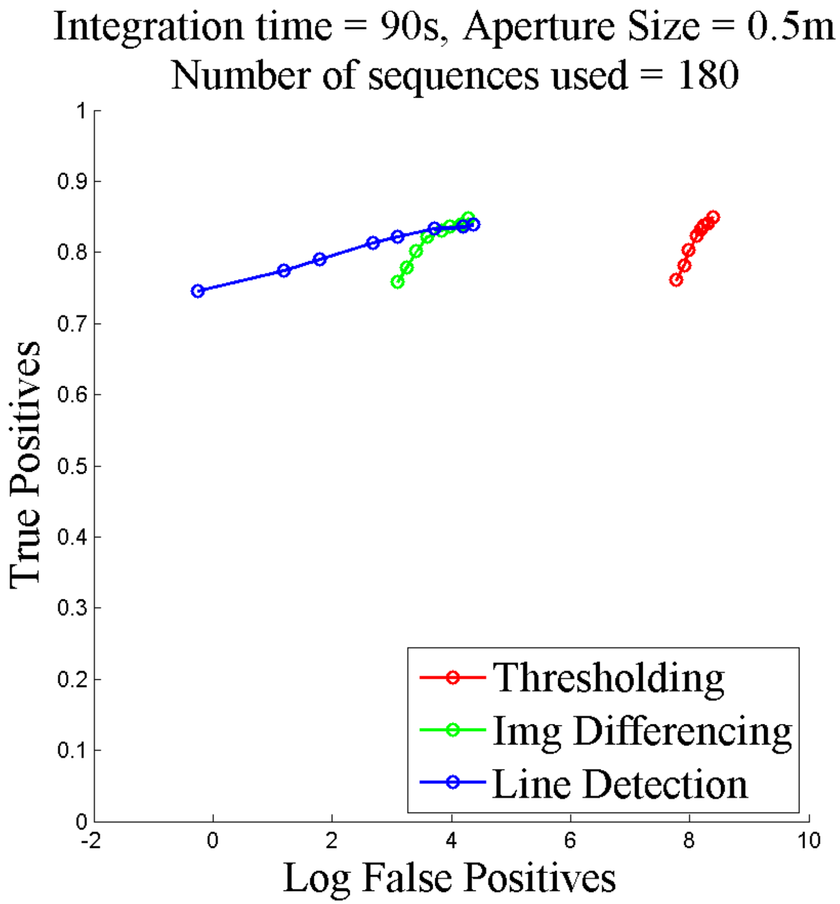
# ROC as a Function of Distance

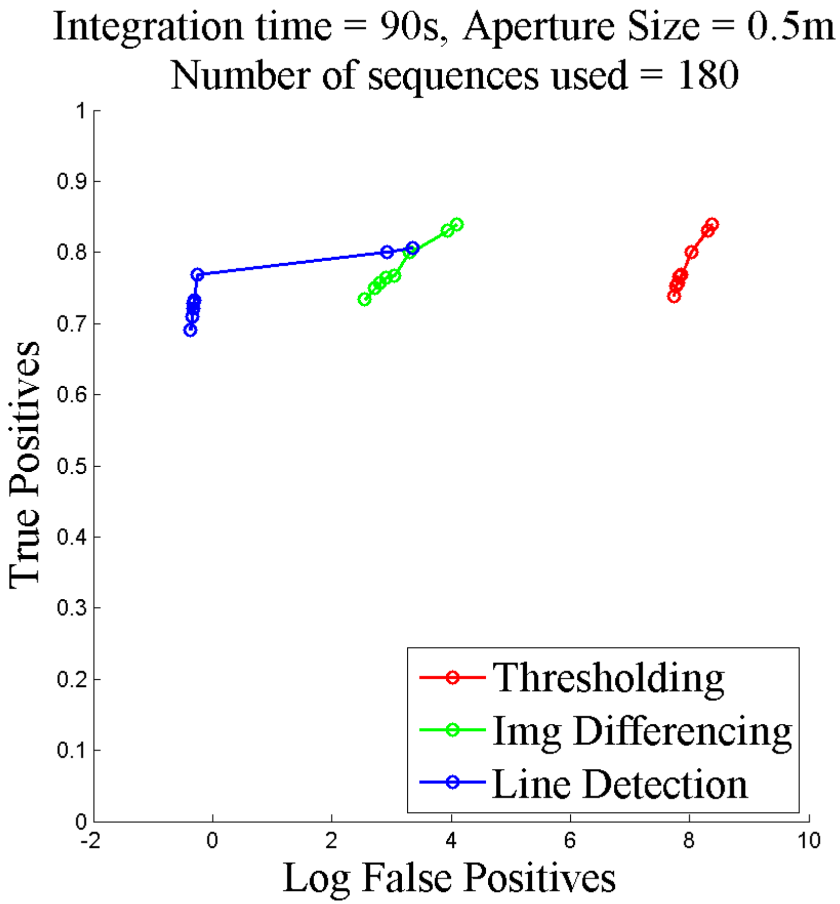



Left: Asteroid Radius = 50 m, Right: Asteroid Radius = 30 m
4 images per sequence, line threshold = 3

# ROC: Algorithm Stages





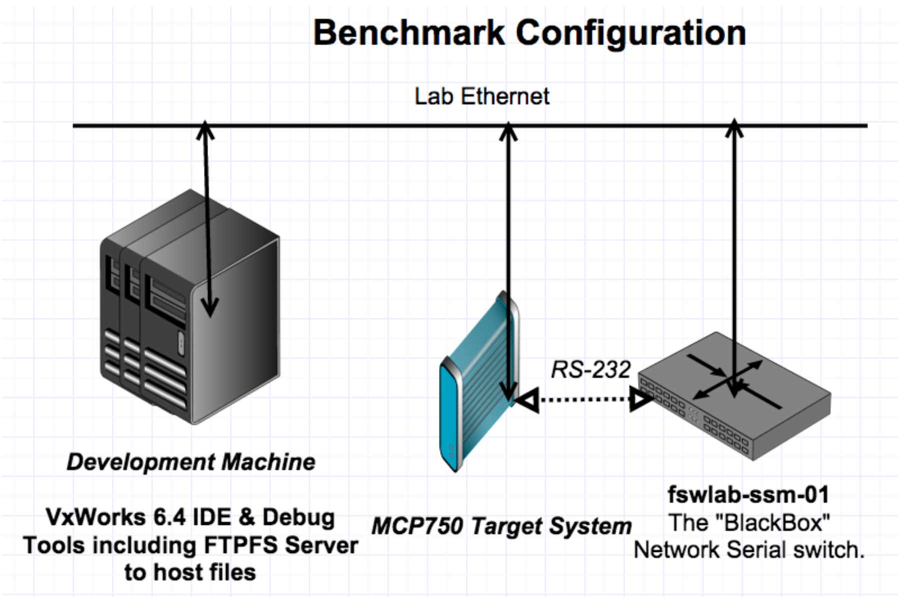

Left: 4 images per sequence, line threshold = 3

Right: 5 images per sequence, line threshold = 4

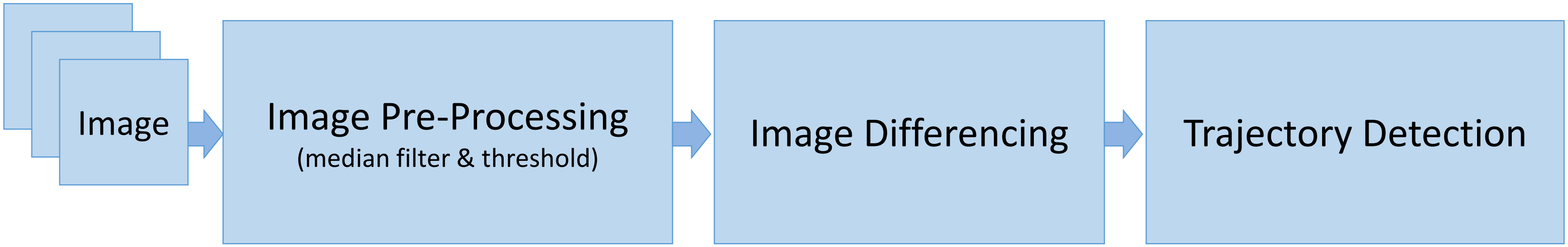
# Implementation Overview

- Algorithm first implemented in MATLAB
- Then Ported to C++ using MS Visual Studio
- Adapted to Linux and VxWorks
- Final version runs as a Real-Time Process (RTP) in VxWorks 6.4

- All benchmarking performed using flight qualified equivalent:
  - VxWorks 6.4
  - Commercial Motorola PPC Boards (MCP750)



# Computational Performance




| MCP750 Measurements | | | | | | |
|---|---|---|---|---|---|---|
| MCP750 | Clock Speed | Image pre-processing (median filter) | Image pre-processing (threshold) | Image Differencing | Trajectory Detection | Sum (avg) |
| 02 | 367MHz | 4.135 sec | .1 sec | 41.85 sec | 0.01 sec | **46.1 sec** |
| 04 | 233MHz | 6.5 sec | .16 sec | 65.59 sec | 0.04 sec | **72.3 sec** |

- The MCP750 processors each have 128MB RAM and ran an identical image under VxWorks 6.4
- Un-optimized and un-compressed application Binary is 1.2M

# Algorithm Capabilities: Summary

- Asteroids of radius 80m and larger are detectable even at 0.4 AU from spacecraft.
- Asteroids of radius 50m are detectable at 0.1, 0.15, and 0.2 AU from spacecraft.  Detection is more sensitive to the threshold used.
- Asteroids of radius 30m cannot be seen for distances >= 0.3 AU. For smaller values of distance (0.25 AU, 0.2  AU, 0.15 AU and 0.1 AU), the detection improves, but remains sensitive to the threshold.
- Even at 0.1 AU, an asteroid smaller than 30m is not consistently detectable.

# Ongoing/Future Work

- False positive reduction
  - Use additional images in sequence
  - Use Machine Learning to detect “good” vs. “bad” triplets
  - Trajectory validation to filter known asteroids

# False Positive Reduction

- SVM (Support Vector Machine)s to detect true trajectories

- Features & True Labels
  - Take 5x5 windows around detections to form a feature vector of dimension 75 or 100.
  - Use known asteroid ground truth as 0/1 labels

- Train the SVM using a portion of the data

- Validate on the remaining test data

# False Positive Reduction SVM results

- Data source - 180 image sequences generated using aperture size = 0.5m and integration time = 90s
- 10 fold cross-validation using SVM
- Kernels used – linear, chi-squared, radial basis function(rbf)

Quadruplets with line threshold = 4

| Kernel | Overall accuracy | True positive accuracy | False positive accuracy |
|---|---|---|---|
| linear | 99.87% | 99.41% | 100% |
| chi-squared | 99.84% | 99.28% | 100% |
| rbf | 100% | 100% | 100% |

# Ongoing/Future Work

- False positive reduction
  - Use additional images in sequence
  - Use Machine Learning to detect “good” vs. “bad” triplets
  - Trajectory validation to filter known asteroids
- Validation against space based imagery
- Validation against known asteroids
- Algorithm optimization to more refined flight characteristics
- Other parameter tuning/optimization
  - Use linear regression to find the optimal threshold for a given set of telescope parameters

# Thanks!

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Team Members and Affiliations:

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- Michelle Chen, JHU/Applied Physics Laboratory
- Phillipe Burlina, Ph.D. JHU/APL and Associate Research Professor, Johns Hopkins University, Department of Computer Science
- Avigyan Sinha, doctoral student at Johns Hopkins University
- Bruno Jedynak, Ph.D. Associate Research Professor at Johns Hopkins University
- Andy Rivkin, Ph.D. JHU/Applied Physics Laboratory
- Justin Atchison, Ph.D. JHU/Applied Physics Laboratory
- Nishant Mehta, JHU/Applied Physics Laboratory
- Zach Fletcher, JHU/Applied Physics Laboratory
- David Edell, JHU/Applied Physics Laboratory
- Christopher Krupiarz, JHU/Applied Physics Laboratory