RANSACing Optical Image Sequences for GEO and near-GEO Objects

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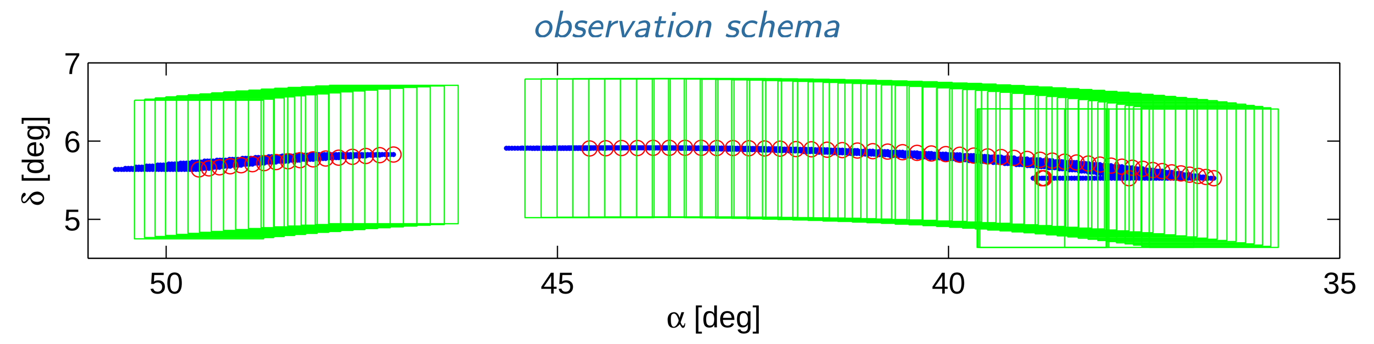
Abstract: Can prior information on the consistency of image tracks and Bayesian modeling bring the performance of image primitive object detection and linking methods closer to the image stacking methods? The answer is positive: It brings it half way from the LINE method [1] to the FPGA Stacking method [1].

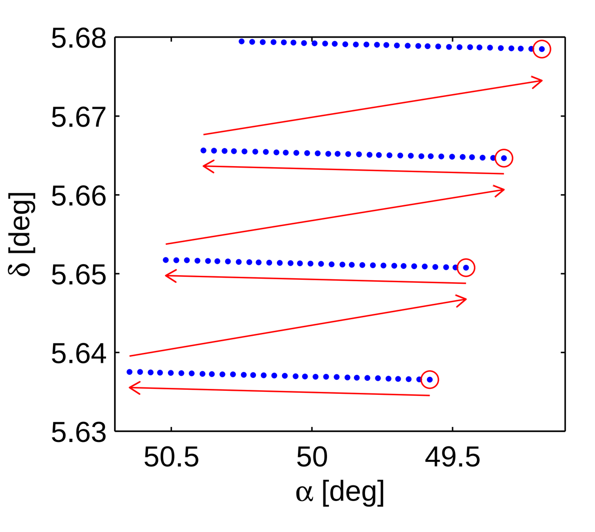
Data

- 50 cm TAOS sensor from Lulin observatory, Taiwan
- FOV 1.3°× 1.3°, 2049 × 2047 pixels, 16 bit
- 3 Days (2011–10–20, . . .), about 5600 images
- the telescope points at a fixed intertial point near the GEO region
- batch: 29 images, 8.8 s intervals, 5.9 s exposures, no sidereal tracking; then reset

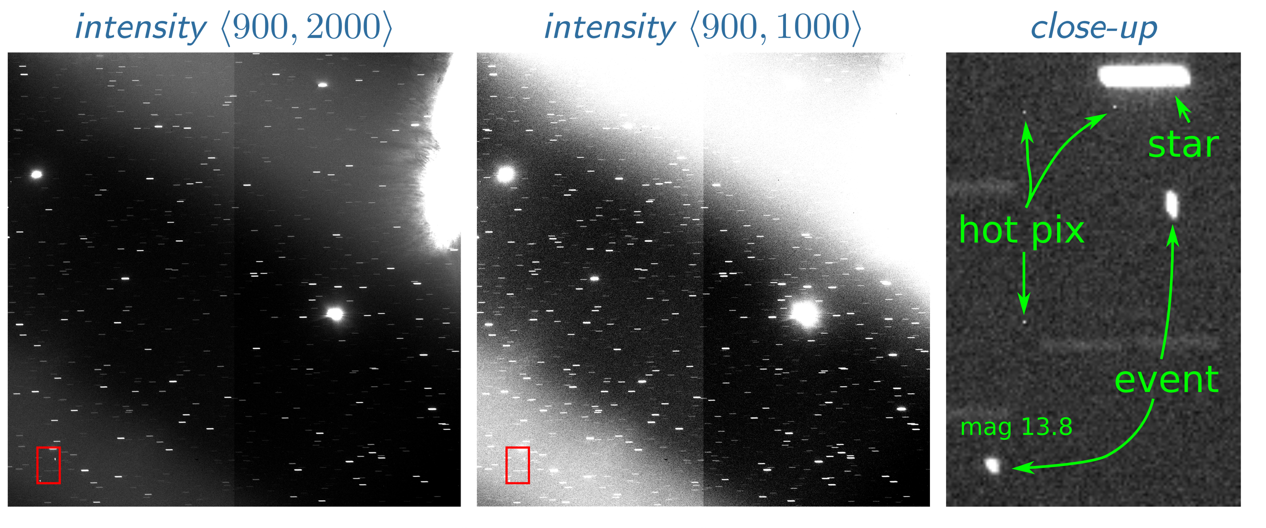
observation schema



observation schema detail



intensity ⟨900, 2000⟩ *intensity ⟨900, 1000⟩* *close-up*



example of data with artifacts emphasized

Registration

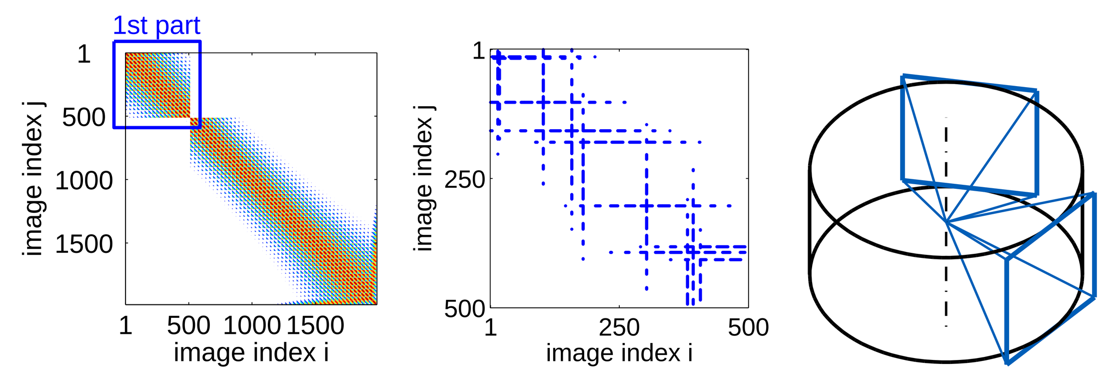
registering stars

- telescope as a calibrated projective camera

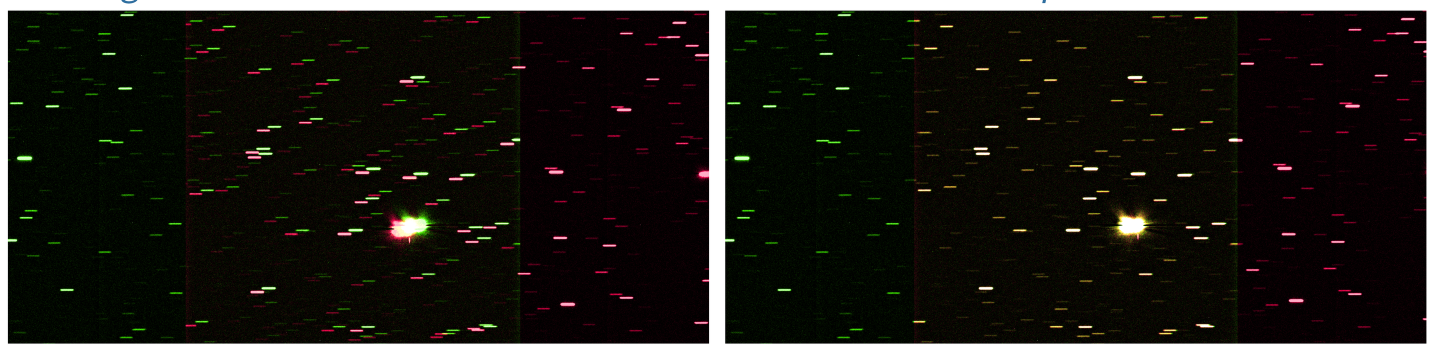
$$\mathbf{H}_{ij} = \mathbf{K}\mathbf{R}_j\mathbf{R}_i^{-1}\mathbf{K}^{-1}$$ mapping between images i, j

- initial rotations from FITS headers insufficient
- optimisation of rotations over the maximum spanning tree of the field-of-view overlap graph
- all images warped onto a common cylinder

pairwise overlaps *MST (1st part)* *registration cylinder*



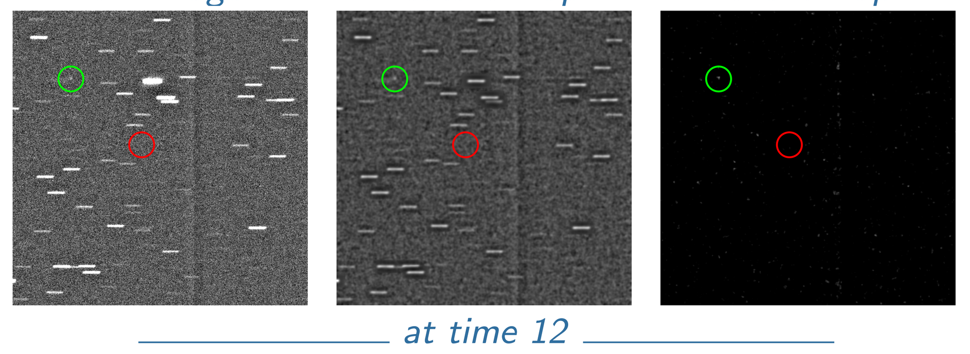
registered with initial rotations. . . *. . . and with optimized rotations*



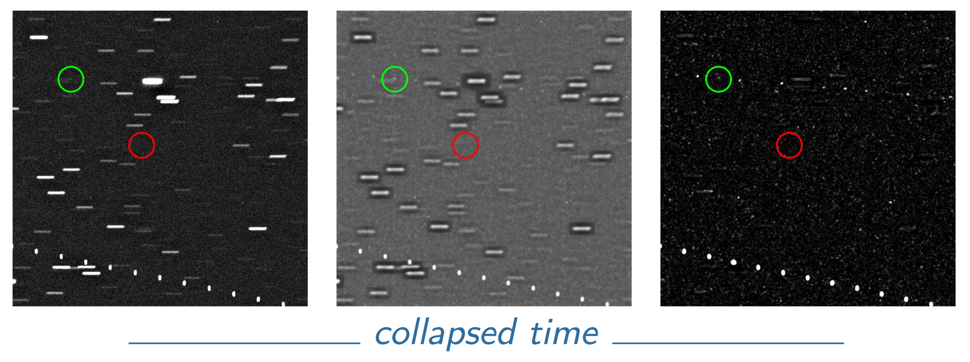
all data: RMS error 2.8 px. . . *. . . RMS error 0.8 px*

Image Features, Temporal Events, Primitives

raw image *feature map* *event map*

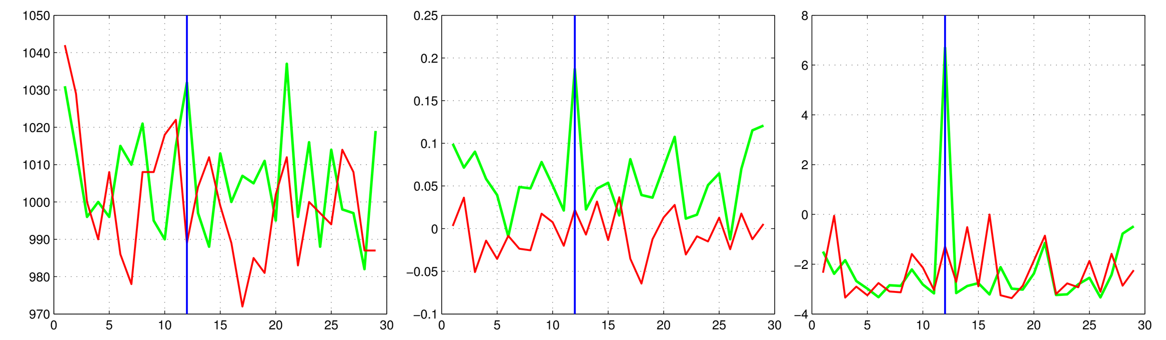


at time 12



collapsed time

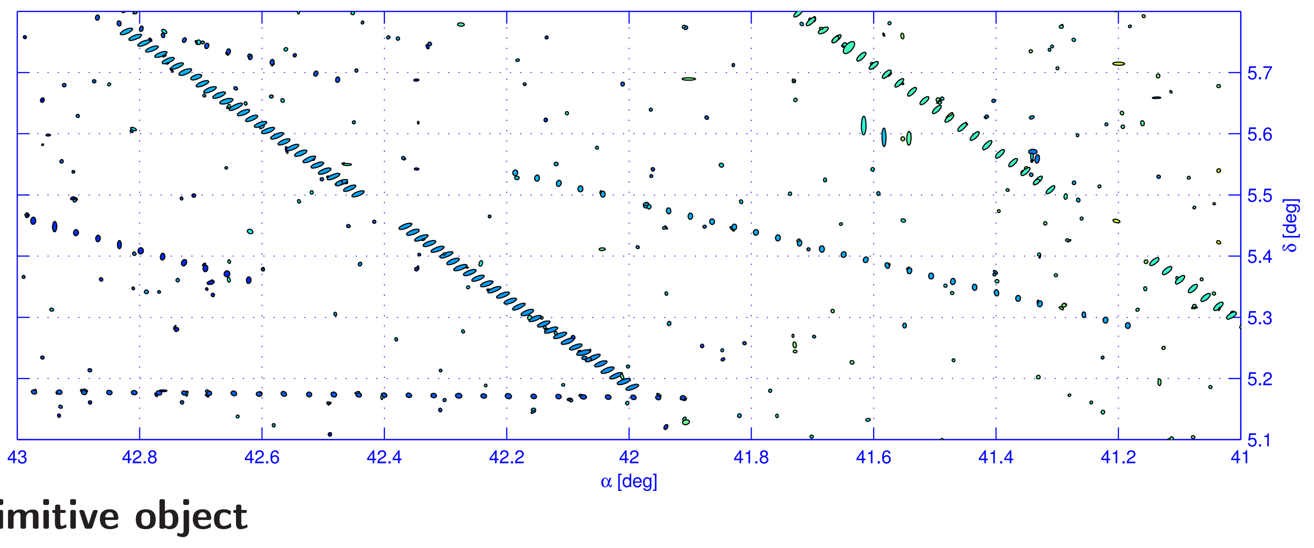
raw image *feature map* *event map*



temporal profiles

- two locations:
  1. high-magnitude event at time 12 (green)
  2. random (red)
- contrast of the event improved in feature map
- star background suppressed in event map

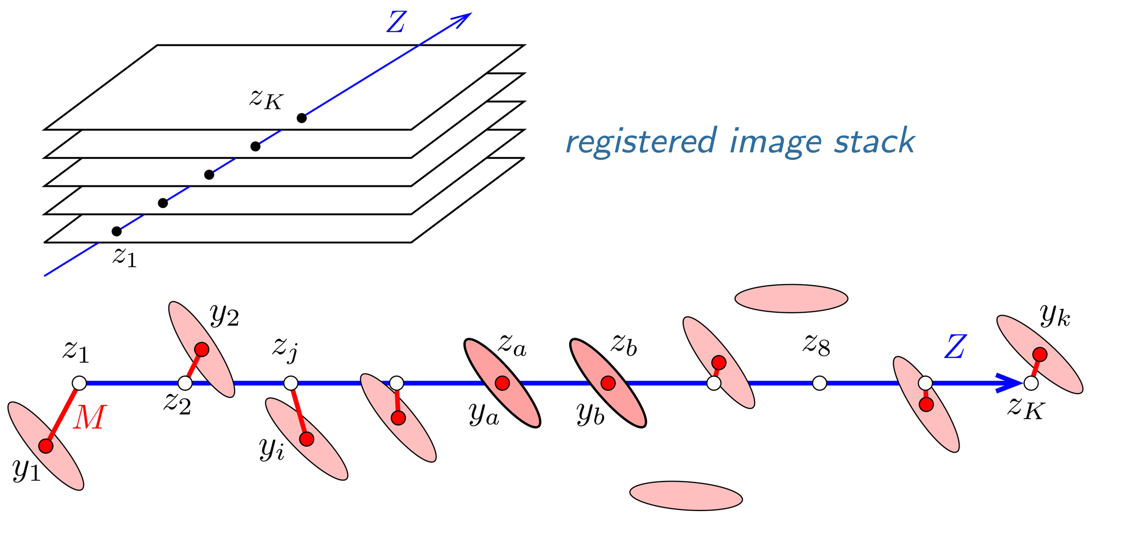
primitive objects after event map segmentation (weak ones removed for clarity)



primitive object

- centroid location in global space and time
- relative magnitude
- elliptical approximation + raw image patch

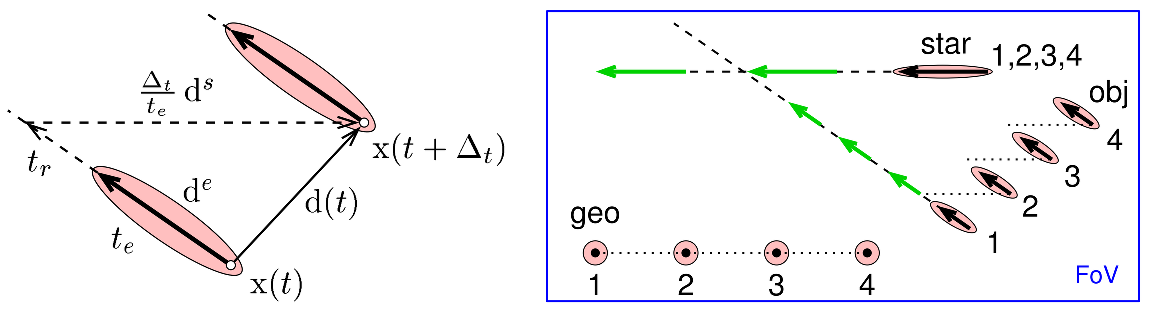
Sequence Detection



- primitives y_a, y_b propose a line Z in space-time
- all primitives are matched to Z by M and classified as inliers/outliers wrt the line by Maximum Likelihood
- line support $s(M, Z)$ is calculated (see the paper)
- efficient: k-d tree search → 50 proposals per sec

Line Support Terms:

1. data model: geometric errors (left), radiometric differences
2. track speed model (below)
3. hot pixel track model (see the paper)



Primitive length $\mathbf{d}^e$ is consistent with track spacing $\mathbf{d}$:

$$\mathbf{d} = \frac{\Delta_t}{t_e}(\mathbf{d}^e + \mathbf{d}^s)$$

t_e – exposure time
Δ_t – inter-frame time interval
$\mathbf{d}^s$ – sidereal motion vector (in image)

Multi-track RANSAC Procedure
(input: primitives D, output: track list $\mathcal{Q}$ of maximal length k)

1. Initialize: Pool of all outliers $O := D$, empty priority queue $\mathcal{Q} := \emptyset$, unsuccessful proposal counter $c := 0$.
2. Propose a random space-time line and compute the track sequence Z (see left).
3. Find the best matching M from Z to the pool O.
4. Compute support $s(M, Z)$.
5. Increment the counter $c := c + 1$.
6. if $s(M, Z) > \min \mathcal{Q}$ then
   (a) if length $\mathcal{Q} = k$ then remove the lowest-priority element from $\mathcal{Q}$ and return its primitives to O,
   (b) admit (M, Z) to $\mathcal{Q}$ with priority $s(M, Z)$,
   (c) remove the set of matched primitives M from O,
   (d) reset the counter $c := 0$.
7. Repeat Steps 2–7 until $c > c_{\text{stop}}$.
8. Return the queue $\mathcal{Q}$.

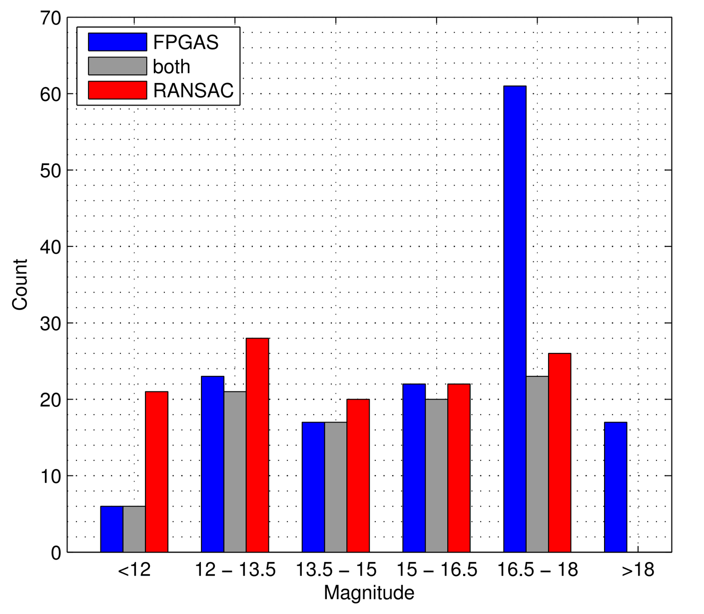
- the number of iterations c_{stop} is not dependent on $|D|$

Results

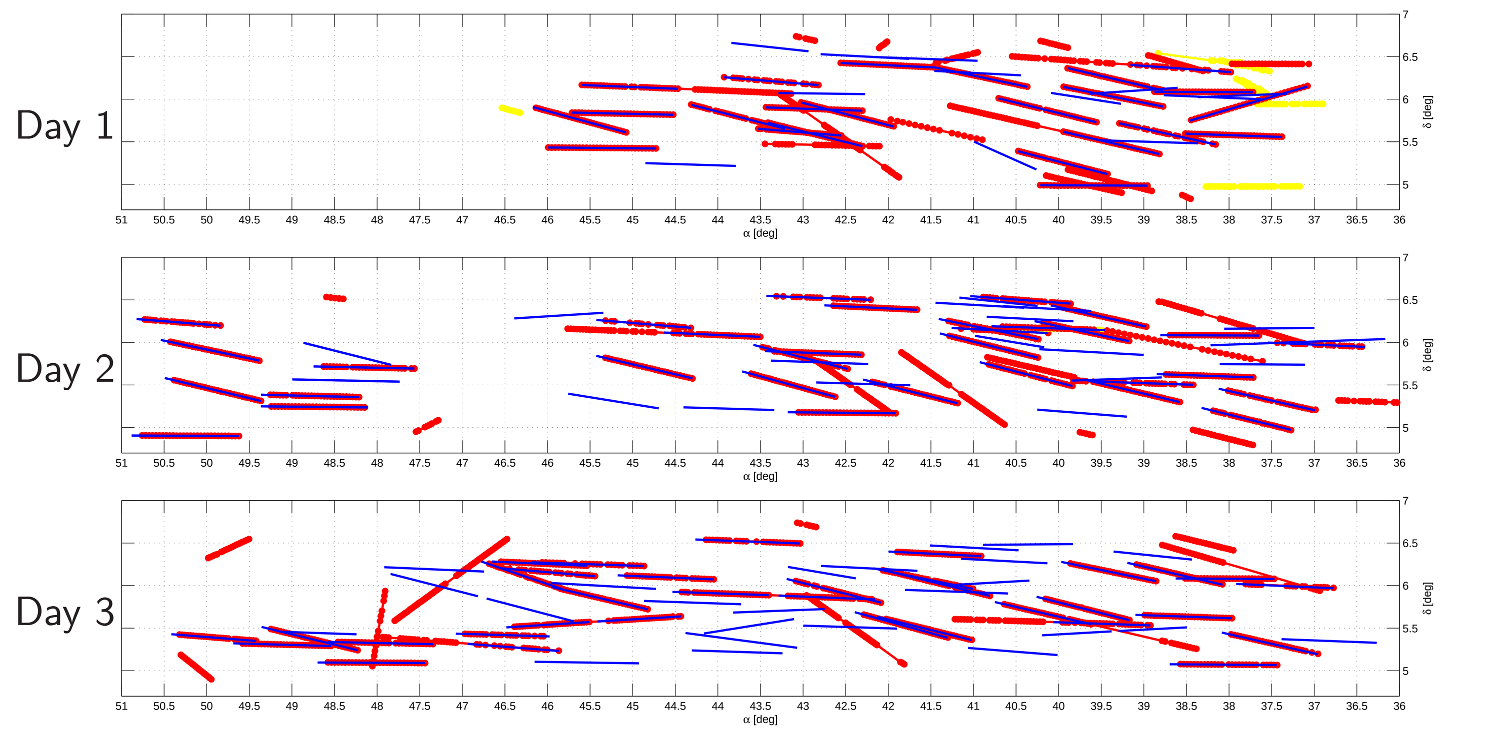
data summary			track detection counts by method			
day	images	primitives	RANSAC	FPGAS	both	false pos.
1	1 584	78 970	35	37	23	5+2(hot)
2	1 980	91 461	42	51	32	1(hot)
3	2 250	105 894	40	58	33	0
tot	5 814	276 325	117	146	87	5+3(hot)

- no ground truth data
- comparison with FPGA Image Stacking method (FPGAS) [1]
- FPGAS detects more tracks in high magnitudes
- RANSAC detects more shorter tracks
- compare the histogram with [2]

detections per magnitude



detections: *red: RANSAC (proposed); yellow: RANSAC FP; blue: FPGAS [1]*



Conclusions

We have tested RANSAC method on a dataset sufficiently large for obtaining predictive performance figures. The results were compared with FPGAS, which is the best performing method that was run on the same data [2]. The proposed RANSAC method is stronger than FPGAS in detecting short tracks and tracks entering the FoV in the middle of the sequence. The FPGAS method is stronger in detecting high-magnitude tracks. The discrepancy can be addressed within the RANSAC framework.

References

[1] T. Yanagisawa and H. Kurosaki, "Detection of faint GEO objects using JAXA's fast analysis methods," *Transactions of the Japan Society for Aeronautical and Space Sciences, Aerospace Technology Japan*, vol. 10, no. 28, pp. Pr_29–Pr_35, 2012.

[2] T. Yanagisawa, H. Kurosaki, H. Banno, Y. Kitazawa, M. Uetsuhara, and T. Hanada, "Comparison between four detection algorithms for GEO objects," in *Proceedings of the Advanced Maui Optical and Space Surveillance Technologies Conference*, 2012.

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Supported by the Missile Defense Agency (USA) and by the Czech Science Foundation. Special thanks go to Toshifumi Yanagisawa of JAXA.

presented at AMOS 2013