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Applications of the Hough Transform for Detecting Moving Objects in Astronomical Data

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Introduction

The problem of detecting moving objects in astronomical data can be reduced to identifying points along a line or arc in a series of images over time. Standard methods for finding lines in such data can be prohibitively computationally expensive as the data size increases.

The **Hough Transform** is a technique used in image processing to identify such geometric shapes in static images.[1] We explore the application of the Hough Transform to astronomical data to identify possible moving objects across multiple epochs in a computationally efficient manner.

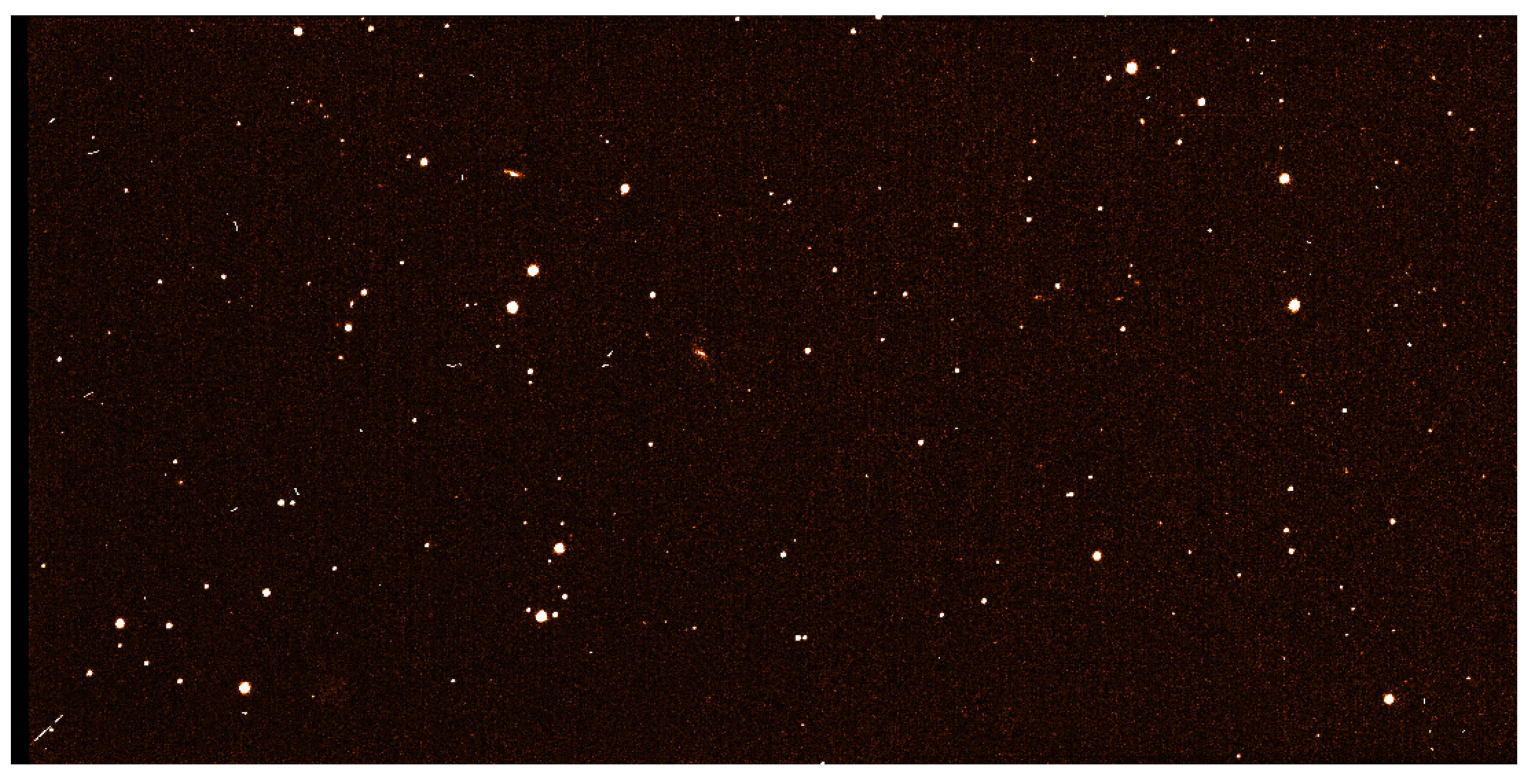


Figure 1: Portion of image from single CCD

The Hough Transform

The standard **Hough Transform** (HT) parameterization is

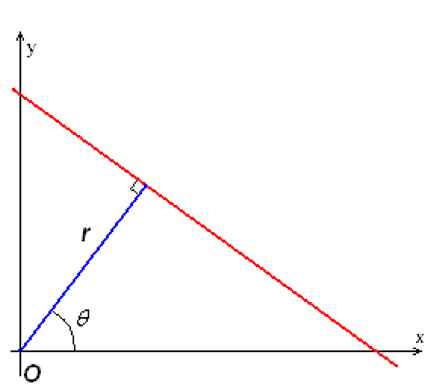


Figure 2: Hough Parameterization

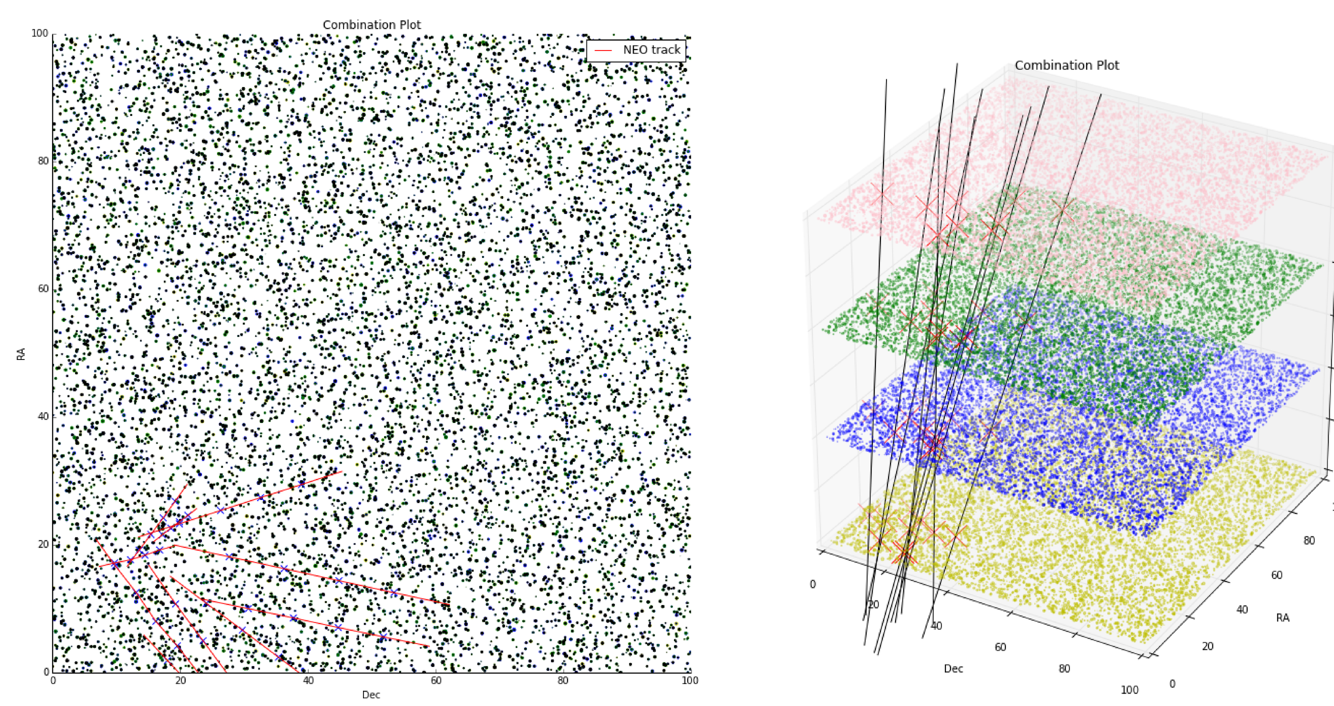
$$\rho = Xcos(\theta) + Ysin(\theta)$$

where ρ and θ represent the distance of the normal vector from the origin and the angle it forms with the X axis.

Using this transformation, a straight line in the XY space corresponds to a single point in the Hough Space. For each point in XY, we calculate $\hat{\rho} = x_i cos\hat{\theta} + y_i sin\hat{\theta}$, $\forall \hat{\theta} \in [0, \pi)$ and increment a corresponding accumulator bin. The local maxima in the accumulator then correspond to likely lines.

Data

We employ our methods initially on synthesized data as shown in Figure 3. We generate nearly 50k points over 4-8 epochs including both stationary objects and noise, and ~5-10 simulated moving objects.



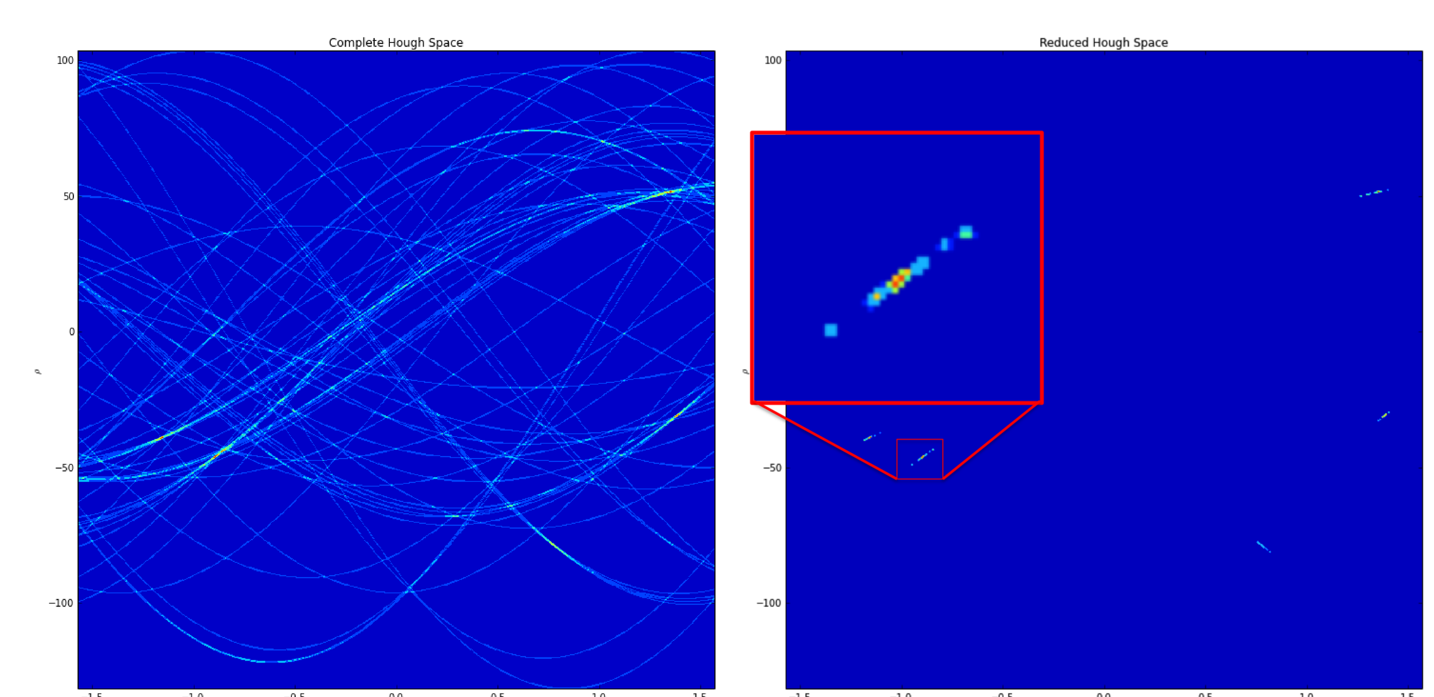
Synthetic data with tracks   synthetic data in 3D

Figure 3: Synthetic data with simulated moving objects

To effectively search this data for moving objects, we eliminate stationary objects through a custom binning procedure and conduct basic noise reduction. For our sample data, this eliminates over 90% of the initial points from consideration.

Methods

The Hough Space for sample data with 5 simulated moving objects within 1000 stationary points is shown below. We use 0.25 degree increments from $\theta = [-\pi/3, \pi/3]$. To reduce the space, we remove the co-linearity within each epoch and remove low value bins.



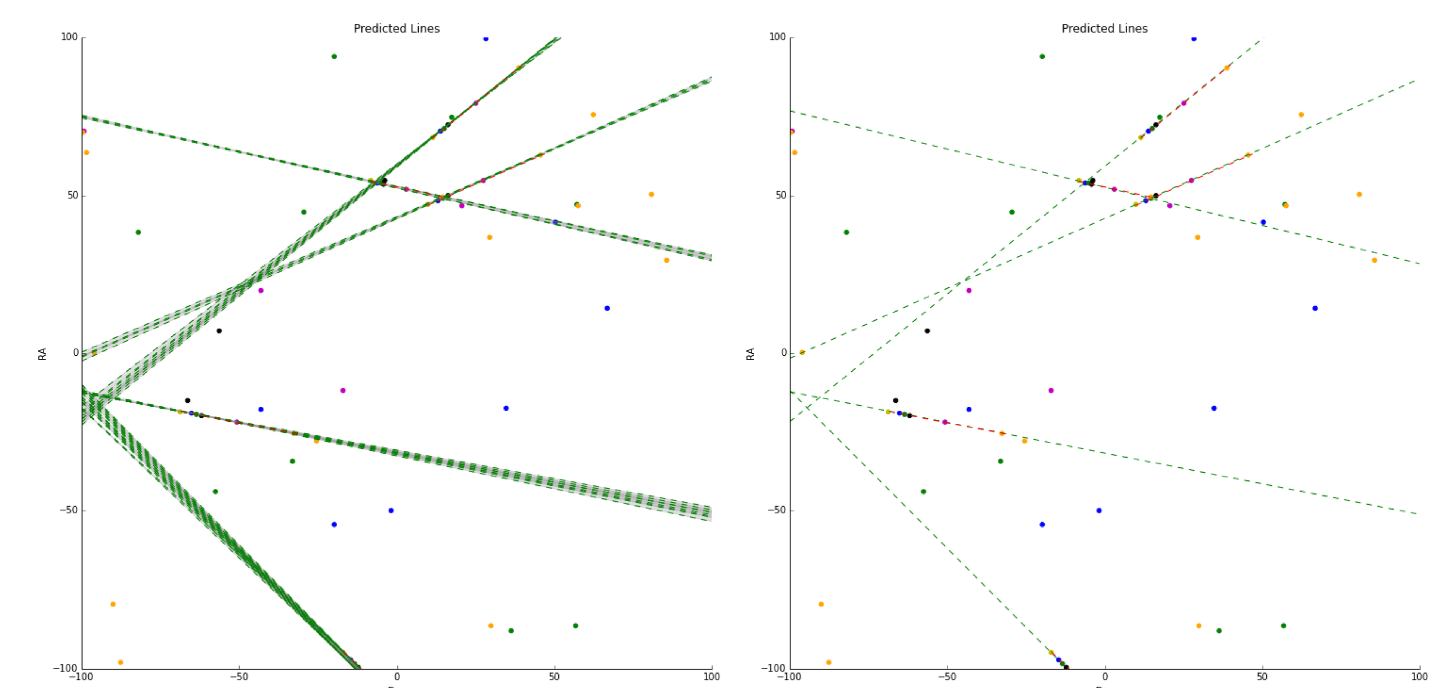
Complete Hough Space   Reduced Hough Space

Figure 4: Hough Space Reduction

To extract the local maxima from the Hough Space, we fit an N-component Gaussian Mixture Model using Bayesian Information Criterion to identify the most likely number of mixture components.

Results

The resulting predicted tracks are shown in the figure below, with the top 25 lines from the reduced binned data and the corresponding lines from the GMM fit. In this sample, the predicted tracks capture all 5 simulated moving objects.



Predicted tracks from reduced Hough Space   Predicted tracks from GMM fit

Figure 5: Predicted tracks

The Hough Transform works well when applied to images with less than ~500 objects per epoch. False positives increase with for images with higher noise.

In ongoing work we are applying our method to data from the Panoramic Survey Telescope & Rapid Response System (Pan-STARRS), consisting of nearly 300 observation frames from August 2010 to November 2013.

Conclusions

The Hough Transform is ideally suited for application to more complex data due to computational scalibility, as the algorithm is $O(N)$. While our current results are primarily drawn from sythetic data, they present key insights for application of the Hough Transform to actual astronomical data.

References

[1] R. O. Duda and P. E. Hart, *Use of the Hough Transformation to Detect Lines and Curves in Pictures*. Stanford Research Institute, 1972.

Acknowledgments

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