Novel Segmentation Technique to Enhance Detection of Fast Moving Objects with Optical Sensors

Oleg Gusyatin
MIT Lincoln Laboratory

Abstract

Depending on the mode of operation, an optical sensor records signatures of sidereal and non-sidereal objects as points or streaks. Streaks that result from fast moving objects present a challenge to automated detection algorithms since potential for heterogeneity in the expected optical signature is higher than that of a point-like object due to the fact that energy is spread over a larger number of pixels during integration. Such heterogeneities may arise from object tumbling, atmospheric effects, occlusions, or even focal plane irregularities.
While standard image processing techniques rely on a single estimated threshold applied to a field of view to isolate sidereal and non-sidereal pixels from background it is often the case that objects captured as longer streaks are being fragmented into multiple collections of pixels resulting in inaccurate position predictions. Such erroneous position estimates often cause loss of detection.
Here we present a novel segmentation algorithm that maximizes fidelity of the resulting streaking objects on a focal plane for highly heterogeneous signatures. Our technique is general in that it assumes that any given object's signature is separable from the background by multiple thresholds simultaneously allowing for accurate segmentations in high-noise or even occluded settings. Segmentation algorithm that we propose is based on a dynamic region-growing technique where a decision for including each individual pixel into a given object is made based on both statistical and spatial properties of the object. Such decisions are made dynamically as objects are being segmented.
This segmentation algorithm is robust and its complexity order does not exceed that of standard segmentation techniques, making it an attractive alternative to signal enhancement techniques such as matched filtering. Testing has been conducted on the ground-based acquisitions of Low-Earth Orbit (LEO) satellites where, in certain datasets, number of detected streaking stars has been increased by over 20%. Also, we have observed a significant increase in detection rates of streaking satellites in high-fidelity simulation data from the Space-Based Space Surveillance program.

Keywords: Segmentation, optical detection, space situational awareness.

Introduction

Optical sensors, both ground- and space-based, are currently widely used to detect and track space objects. Generally, telescopes operate by integrating reflected energy onto a focal plane array. In case of a sidereal stare mode of observation, depending on the velocity at which the object is moving, energy associated with the object will spread across multiple pixels. This, effectively, reduced the SNR of the object making it more difficult for automatic detection. Detection capabilities may be exacerbated by the introduction of additional heterogeneity into the object signature. Such has been observed to come from factors such as atmospheric refraction (when imaging from the ground) or object tumbling during the integration period. Since optical systems include a digital focal plane array (DFPA), infidelities in the latter may be a cause of loss of useful signal. Phenomena commonly referred to as hot and dead pixels on a DFPA tends to be compensated for by simply excluding such pixels from processing as they do not capture necessary information. Same may be determined for pixels that have saturated during the integration time thus causing them to be discarded. Fig. 1 exhibits a streaking object that happened to have crossed a row of pixels excluded from processing and, thus, creating a spatial discontinuity in the objects signature. Naturally, this is more likely to happen with streaks of longer length such as those produced by higher-velocity LEO objects. Fig. 2 shows a streaking star, captured in rate-track mode of a ground telescope, where texture introduced due to atmospheric effects presents a problem when a single threshold is being applied to segment it from the background. Accurate segmentation, necessary for subsequent detection, association, and tracking, is central to this paper. Next section is dedicated to a brief review of standard methods for segmenting objects where deficiencies of such techniques in view of aforementioned problems will be explained. The following section will describe the proposed approach to mitigated issues presented by standard methods and that has been implemented and is currently deployed as part of Optical Processing Architecture at Lincoln (**OPAL**). Finally, results of applying proposed segmentation approach to data from various ground- and space-based systems will be shown.

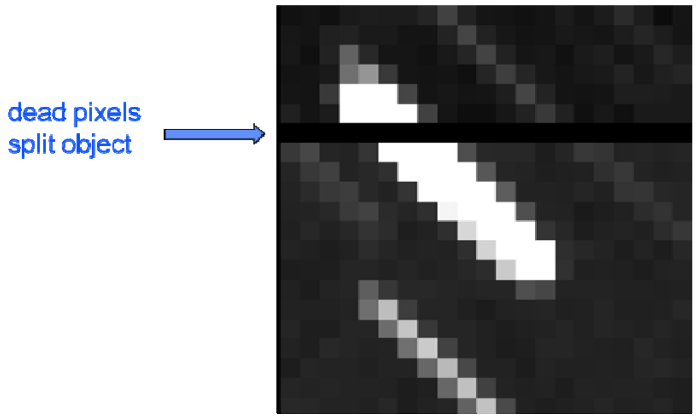

Figure 1: Object signature corrupted by sensor artifact.

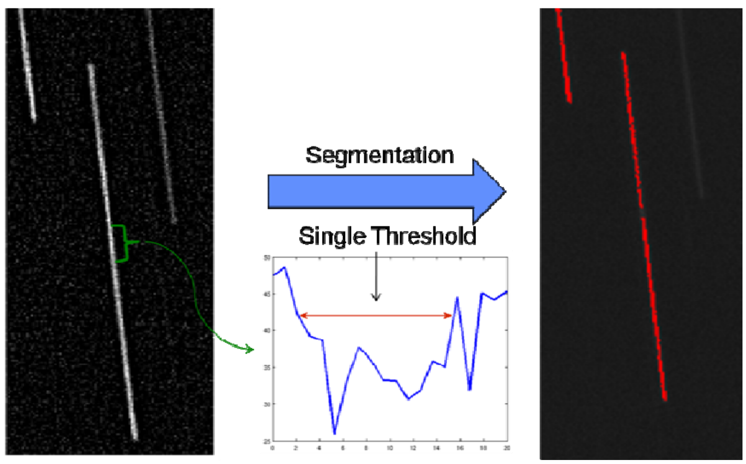

Figure 2: Object heterogeneity poses a problem for single-threshold segmentation methods.

Single-Threshold Segmentation

Techniques that fall under the umbrella of single-threshold methods mainly differ in the way the threshold is estimated. They all, however, share an assumption that there exists a single threshold that separates foreground objects from the background [1]. It has to be noted that in a general case such assumption does not hold and objects tend to span a significant section of the dynamic range. Consider Fig. 3, where a 1D intensity cross-section of an object (depicted in green) fails to be accurately captured by a potential threshold due to a presence of a strong cross-track gradient. Situations like this are quite common and techniques such as high-pass filters are employed to alleviate the issue (see Fig. 3, blue profile). Some common methods for estimating a segmenting threshold (foreground-background) include Otsu's algorithm [2], where ratio of between-class and within-class intensity variance is being maximized. Another approach uses a cumulative density function (CDF) to mark as foreground pixels that comprise the top N percent of the overall image's energy. In our case, such percentage is usually small as there background pixels dominate. A third method determines threshold by estimating the full-width-half-max (FWHM) of the image's background distribution and uses a multiple k thereof to adjust threshold for a particular image (see Fig. 4). This is particularly useful since background intensity distribution is often skewed away from being normal and a robust estimate of its energy is needed.

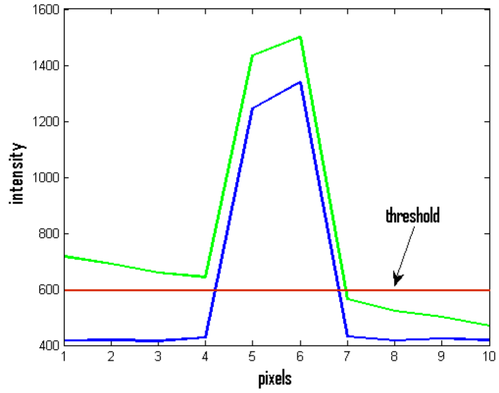

Figure 3: Cross-track gradient and single-threshold segmentation

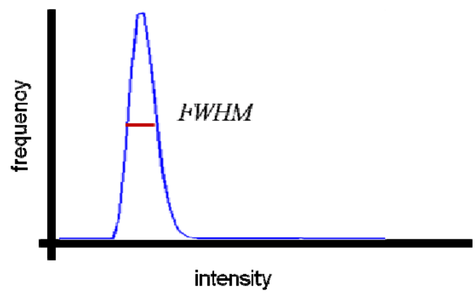

Figure 4: FWHM used to estimate background distribution.

These techniques generally provide a good estimate of the segmentation threshold but fail to account for local scale heterogeneities within streaking objects. We proceed with description of the proposed segmentation approach.

Region Growing-Based Segmentation

It is evident from the examples above that segmentation should support multiple thresholds within an object at the same time preserving its spatial contiguity. Conveniently enough, space objects observed with optical sensors can be viewed as point-sources convolved with a point-spread function and having some velocity. This allows us to employ a scheme where an object can be "grown" starting with a highest intensity pixel (we refer to it as a *seed* later) and by adding subsequent neighboring pixels until a criteria-based decision is made to stop. Such procedure is then repeated until there are no more *seed* pixels available (see Fig. 5).

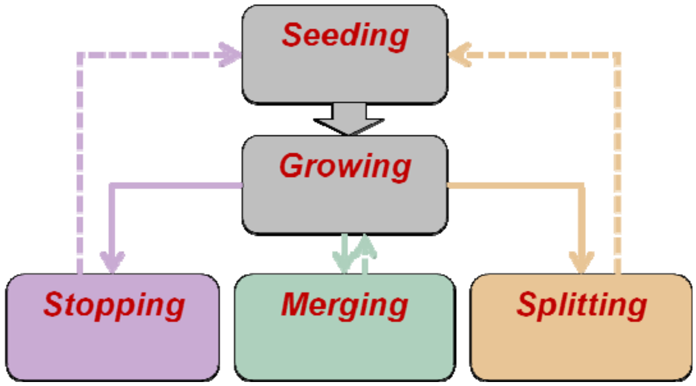

Figure 5: Region-growing algorithm.

Individual steps of the algorithm are further discussed in greater detail.

Seeding

Seeding a region for growth involves picking a highest available intensity pixel (image pixels are sorted in descending value order) under the condition that its value is higher than that of the global background estimate ($FWHM$ method is used here). Such condition prevents from seeding regions within the background. Pixels picked as *seeds* or added to a region are eliminated from further consideration. (see Fig. 6)

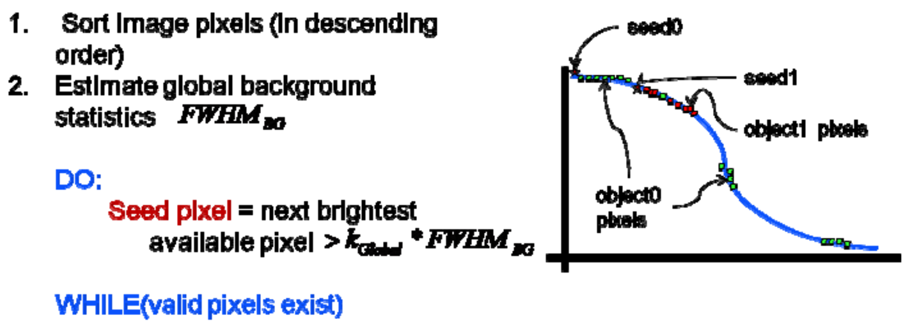

Figure 6: Seeding algorithm.

Growing

Rule to add a pixel to an existing region demands that a candidate pixel must be a neighbor (in 8-connected sense). Also, the preference is given to the candidate P whose value is closest to the region's mean value [3]:

$$P = \arg\min_{i} \left[\left| candidates(i) - \mu_k \right| \right]$$

This ensures a growth that is smooth in intensity which usually translates into a smooth spatial growth of an object. Fig. 7 illustrates a sample growing process.

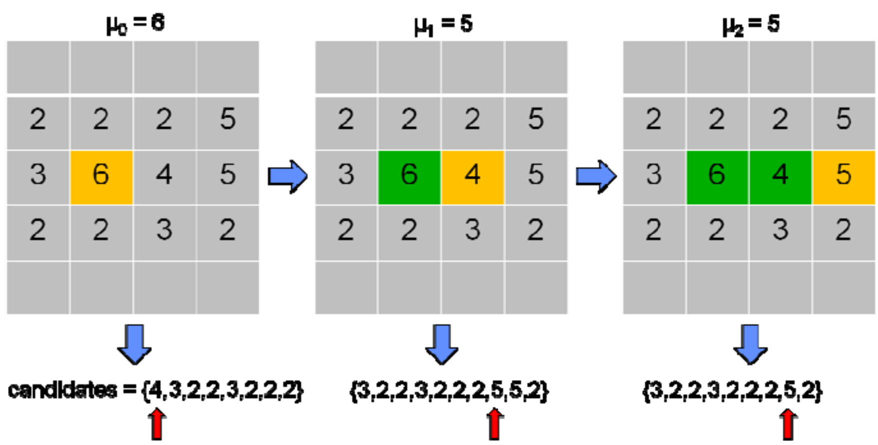

Figure 7: Growing algorithm. Starting with a *seed* (far left), two pixels are added.

Stopping

An important step in any unsupervised clustering approach is a point of convergence or stopping. Before a candidate pixel is added to the region, a number of criteria are evaluated to decide whether the addition should proceed. One of the conditions under which a pixel would not be added to the region is when a pixel is determined to belong to background rather than the object. In our current implementation such decision is made by evaluating a current pixel’s value against a statistical sample of background in its immediate neighborhood. Background distribution is sampled and estimated from a structured disk (SDE) (see Fig. 8) using the $FWHM$ estimate.

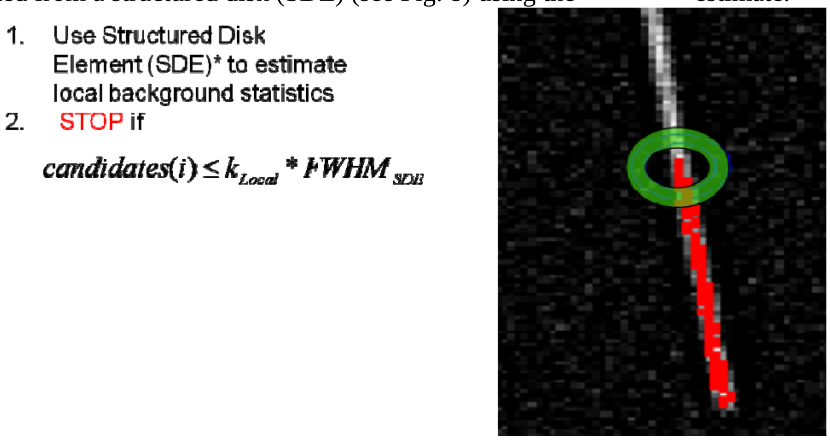

Figure 8: Stopping Algorithm. SDE (shown in green) samples local background distribution. Pixels show in red are already part of the current region.

Merging

During growth it is possible to encounter an existing, processed, region. If such an event occurs, an agglomerative approach is taken and both regions are merged into one (unless the existing object has been previously split; see ***Splitting*** below). Two regions are merged if they share at least one neighboring pixel. See Fig. 9 for illustration.

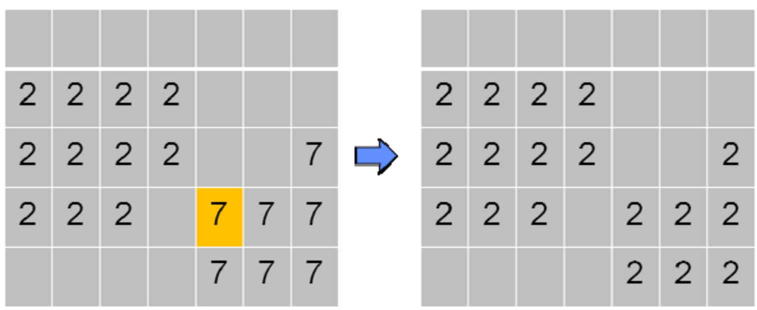

Figure 9: Merging Algorithm. Two regions are being merged as soon as contact is detected.

Splitting

Merging of all neighboring objects on the scene does not necessarily produce proper object separation (see Fig. 10). Constraints on object’s texture statistics are placed in order to prevent objects “leaking” across connecting intensity ridges. It is assumed that each object has some level of heterogeneity and as growth proceeds, quantified by intensity coefficient-of-variation (CV):

$CV(k) = \frac{\sigma_k}{\mu_k}$, where k is the set of pixels in the region.

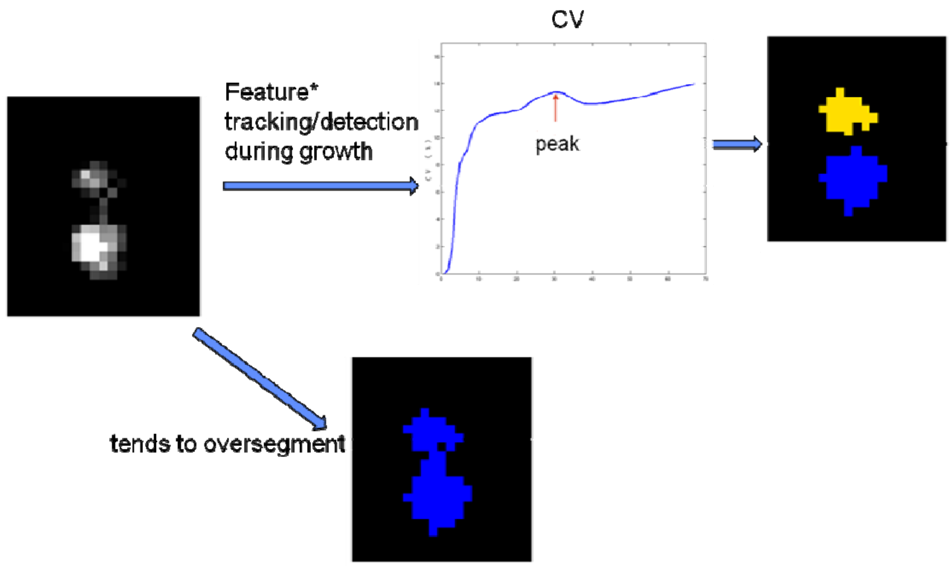

Figure 10: Splitting Algorithm. Dynamic texture feature tracking is employed to detect oversegmentation.

A moving window is employed to detect a peak in this texture feature indicating that growth procedure has travelled across a set of pixels that separates two relatively texture-homogeneous structures. At this point growth is interrupted and region is marked as being *split* such that no other object can be merged with it.

Note that since only a small fraction of the image's pixels is being used for processing and complexity of the processing is roughly $O(N)$, where N is the number of pixels, this algorithm is an attractive candidate for segmentation.

Results

Testing was conducted using data from MIT Lincoln Laboratory Experimental Test Site, Socorro NM as well as from MIT Lincoln Laboratory Firepond Facility, Westford MA. (see Fig. 11)Rate-tracking mode was used to generate large numbers of streaking stars. Proposed segmentation approach was evaluated against standard ones to show that detection rate for contiguous streaks increased 22% (average over approximately 1300 framesets).
Tests were also conducted with Space-Based Space Surveillance (***SBSS***) High Fidelity Simulation Data to show a 56% increase in detection of higher velocity streaking targets and nearly 60% decrease in overall false alarm rate (present mainly due to fragmented long streaks).
Algorithm has been implemented and deployed as part of Optical Processing Architecture at Lincoln (***OPAL***).

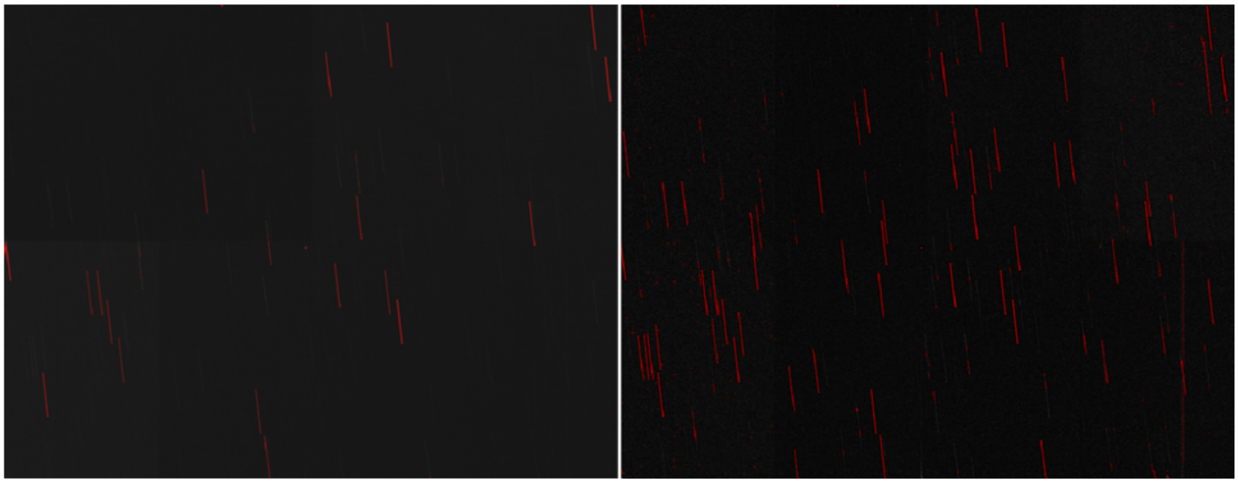

Figure 11: Streaking star data collected at MIT Lincoln Laboratory Experimental Test Site, Socorro NM. Standard segmentation (left), proposed segmentation (right).

References

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