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Detecting Bright Points in Hinode XRT Lightcurves

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Abstract

One of the greatest challenges in solar coronal physics is to obtain a statistically complete sample of short duration events like coronal bright points. Such samples are necessary to fully characterize the properties of these events and understand the physical basis of such phenomena. Datasets are best acquired automatically, without manual intervention, in order to avoid introducing observer biases. We evaluate several algorithms for detecting flare events in time series data. One algorithm determines where derivatives of the Gaussian-smoothed lightcurve cross certain thresholds. A second algorithm segments the Loess-smoothed lightcurve between consecutive minima, then joins adjacent segments if their extrema are not statistically distinguishable. A third algorithm is a hybrid of the first two. We generate simulated datasets with similar properties to observed Hinode XRT quiet Sun lightcurves and test each algorithm on these datasets. The performance of each algorithm on the simulated lightcurves is scored according to the rates of false positive (Type I) and false negative (Type II) errors. We use these results to optimize the parameter values of each algorithm. We compare the performances of the algorithms and evaluate the efficiency with which they are able to detect small events. Such evaluations are relevant to properly interpret the observed steepening of the slope of the solar flare energy distribution at small energies.

I. Event Detection Algorithms

Goal Event detection in presence of variable background (e.g. Figure 1), without knowledge of background. Identify start and end time of event.

Three IDL event detection codes:

1. **Detect Peak** Smooths lightcurve with fixed-width Gaussian, looks at where lightcurve derivative crosses given thresholds to find event.
2. **Segment Finder** Multi-scale Loess smoothing on lightcurve, segments lightcurve between consecutive minima, then merges adjacent segments if adjacent extrema are statistically indistinguishable.
3. **Combined** A combination of the first two methods: uses multi-scale Loess smoothing and identifies events with derivative threshold crossing method.

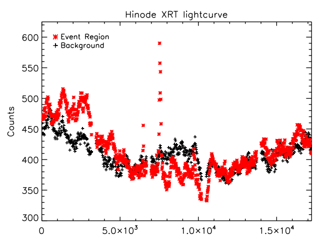

Figure 1 Observed solar lightcurves from flaring region (red asterisks) and nearby background region (black crosses). XRT data provided by P. Grigis.

II. Simulated Lightcurves

To test the performance of the event detection algorithms and find optimal values for the algorithm parameters, we make simulated lightcurves with 0, 1, 2, 4, 8, 16, 32, and 64 events in 1896 time bins (to match the length of our observed lightcurves). The events are the product of a slanted line and a modified Lorentzian (PINTofALE `mk_slant` routine). The event peaks are chosen randomly from a powerlaw distribution with index 1.8, and the core widths are chosen randomly from a Gaussian distribution. The other event parameters (position of peak, rising angle, and beta-profile index) are chosen randomly from uniform distributions. The events are added to a constant background. The mean value of the lightcurve is set to match that of the observed data, and Poisson noise is added. For each number of events we have 1000 simulated lightcurves. An example with 64 events is shown in Figure 2.

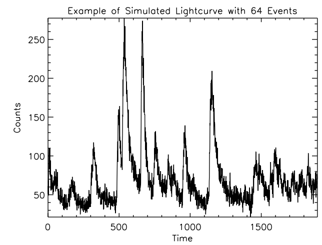

Figure 2 Simulated lightcurve with 64 events added to a constant background. Events are modeled as the product of a slanted line and a modified Lorentzian, and event intensities are chosen randomly from a powerlaw distribution with index 1.8.

III. Calibrating with False Positives

Each of the three event detection codes has one parameter primarily controlling the sensitivity: for Detect Peak and the combined algorithm it is a normalization applied to the threshold values, and for Segment Finder it is the difference threshold S/N for deciding if adjacent extrema are statistically distinguishable. (For Detect Peak and the combined algorithm, increasing the threshold normalization results in a looser detection criteria and therefore more false positives.) To find the values of these parameters which optimize false positives, we run each code on the simulated lightcurves with zero events, varying the parameter values. The results are shown in Figure 3. Based on the length of the simulated lightcurves, we would expect $\sim$2 false positives at the 99.7% significance level. Therefore, we choose optimal values for the event detection codes of

- Detect Peak: threshold normalization = 6×10^{-5}
- Segment Finder: difference threshold S/N = 3
- Combined: threshold normalization = 5×10^{-4}

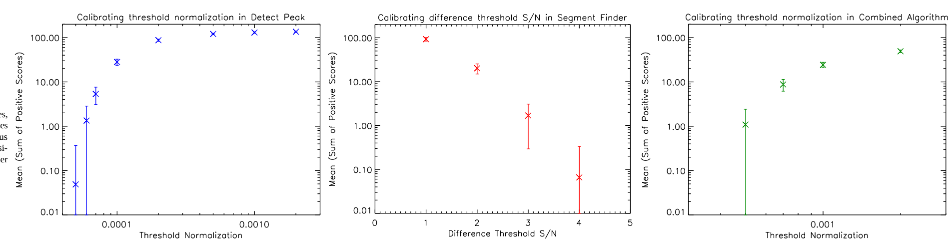

Figure 3 Calibrating the event detection algorithms to optimize false positives, using the simulated lightcurves with zero events. We expect $\sim$2 false positives at the 99.7% significance level. **Right** Average number of false positives versus threshold normalization for Detect Peak. **Middle** Average number of false positives versus difference threshold S/N for Segment Finder. **Left** Average number of false positives versus threshold normalization for the combined algorithm.

IV. Algorithm Performance

Using the optimal parameter values determined in Figure 3, we run the algorithms on a set of 15 lightcurves observed with Hinode XRT (Figure 4, left), and on the set of simulated lightcurves with 64 events (Figure 4, right). The observed lightcurves were manually selected based on the occurrence of one event, but we have extended the analysis to include all possible events. Each of the 15 bright points is widely separated, so the events are independent. Fitting the log-distributions of observed events, we find powerlaw indices of $\approx$ 1.6-1.8.

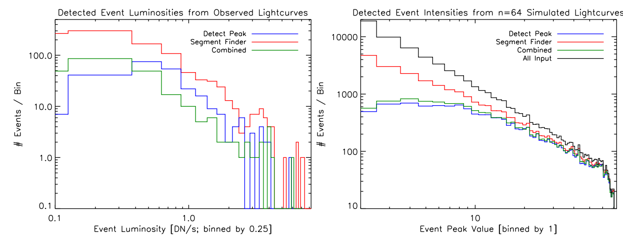

Figure 4 Performance of the algorithms on observed and simulated lightcurves. **Left** Number versus luminosity (DN/s) of detected events in 15 lightcurves observed with Hinode XRT, with sensitivity parameters in each algorithm set to optimize false positives. Fitting the curves above DN/s = 0.3 gives the following powerlaw index values: 1.81 (Segment Finder), 1.77 (Detect Peak), 1.59 (combined). **Right** Number versus peak intensity of detected events in 1000 simulated lightcurves, with sensitivity parameters in each algorithm set to optimize false positives. The black line shows the histogram of all peak intensities in the simulated data set. The algorithms perform equally well for bright events, but the probability of detection decreases for weaker events. This decrease is due to a decrease in sensitivity to weak events (for Detect Peak and the combined algorithm), and also because weak events are undetected when they occur over the same time interval as a stronger event.

V. Summary & Future Work

- We develop a set of simulated lightcurves to test three event detection algorithms.
- Simulated lightcurves with zero events are used to calibrate the algorithms to optimize false positives.
- Compared to the other two algorithms, Segment Finder appears more sensitive to small (peak < 10 counts) events.
- In our sample of 15 observed Hinode XRT lightcurves, quiet Sun bright point events are distributed as a powerlaw with measured index between 1.6 and 1.8.
- To do: investigate the use of a robust Bayesian wavelet-based event detection method, developed by Alex Blocker.

References

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