Probing flare reconnection regions with LYRA and AIA

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Aim of the Project

The motivation for this study is to examine the nature of energy release processes in solar flares. McAteer et al (2007) showed that higher energy bands in RHESSI flare data exhibit more anti-persistence, and are 'burstier' than lower energy bands in RHESSI. This suggests that electrons that are accelerated to higher energies are due to less correlated events in the reconnection region. One possible physical interpretation is that the reconnection region is composed of many different small reconnection regions, and that the higher energy electrons experience many more different reconnection/particle acceleration regions than lower energy electrons.

The analysis of McAteer et al (2007) is partly based on the *Hurst exponent H.* This quantity measures the *persistence* in the data compared to that expected from a purely Gaussian-noisy time-series. If $0.5<H<1$, then the time-series is more correlated than Gaussian random noise, and is termed persistent. Conversely, if $0<H<0.5$, the time-series is less correlated than Gaussian random noise, and is termed anti-persistence.

The idea of studying the persistence of flare time-series is extended to look at pre- and post-flare emission to determine if there is a detectable difference in the pre- and post-flare persistence of the emission. A difference between the pre- and post-flare persistence indicates differences in the long range time-dependence of the emission, which can be interpreted as indicating the presence of different mechanisms in the coronal plasma that cause differences in the behavior of LYRA time-series pre- and post-flare. Any significant differences may lead to the derivation of a flare pre-cursor signal.

All the code developed for this work can be found at https://github.com/wafels/PROBA2-GI-Analysis.

Data preparation

This project takes advantage of pre-existing code packages already written in the R statistical language (http://www.r-project.org). Therefore, LYRA data had to be available to made available to these packages. This was achieved by reading the data into a SunPy (http://www.sunpy.org) session and then using the *rpy2* package (http://rpy.sourceforge.net/rpy2.html) to pass data and results to and from concurrently running Python and R sessions.

Python/SunPy was chosen as the principle data analysis environment since it provides easy to use interfaces to the HEK and to the R statistical package. A considerable amount of time on the project was spent designing an object in SunPy that can be used to store and manipulate LYRA data. It should be noted that the effort to include LYRA data in SunPy inspired several volunteer developers from outside the PROBA2 Guest Investigator community to contribute to the development of time-series data objects in SunPy. The LYRA data object is now a subclass of the more general purpose SunPy time-series data object.

The analysis proceeds as follows. A range of dates is selected. For each day in the range, the LYRA data is downloaded and the start and end times of all flares stored in the HEK is also obtained. This allows us to segment the data into two sets of time-series, a set that contain time-series, and a set that do not. Spikes are detected in the non-flaring time-series and those data are excised.

Dedicated Instrument Campaign

No dedicated instrument campaigns were required for this work.

Preliminary results and discussion

LYRA data from 2012/06/08 to 2012/07/08 was downloaded from the PROBA2 datacenter. Flare occurrence times over the same date range were obtained from the HEK. The data was split as described above. Only time-series of a duration of at least 10,000 observations (500 seconds) or more were analyzed. Further, after a flare, the first 10,000 observations were analyzed, and before a flare, the 10,000 observations just before the flare were analyzed. The rescaled range analysis method (Bassingthwaighte and Raymond, 1994; Oliver and Ballester 1996) from the R package *fArma* (rsFit; see http://cran.r-project.org/web/packages/fArma/index.html) was used to fit the Hurst exponent. As a comparison, results were also generated by replacing the LYRA data with Gaussian noise, and performing the same analysis. LYRA data from channels 3 and 4 were analyzed. The results are shown below.

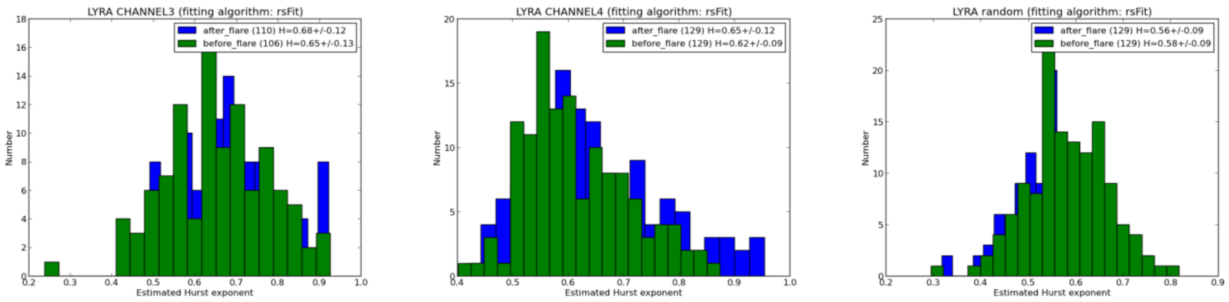

Figure 1: Hurst (H) exponent results. Plot legends give the number of time series of each type in brackets, an estimate of the mean Hurst exponent, and its standard deviation.

The results show that the average Hurst exponents before and after a flare are indistinguishable from each other for both LYRA channels 3 (left plot) and 4 (middle plot) within one standard deviation. However, we also note a slightly higher Hurst exponent in the 'after flare' time-series compared to the 'before-flare' time-series in both channels. A Kolmogorov-Smirnov test was also applied to each pair of distributions. The test showed that the null hypothesis – that the two observed distributions are drawn from the same parent distribution – could not be rejected.

The right-most plot shows the same analysis applied to Gaussian noise time-series with the same sampling as the LYRA channel 4 data. A purely Gaussian time-series has a Hurst exponent of $H=0.5$. These results show a slight bias towards higher values of H. If we accept this bias as present in the analysis method, then the LYRA data-derived plots show evidence for weakly persistent time-series in LYRA channel 3 and 4 data. Therefore pre- and post-flare LYRA time-series are not simply pure, uncorrelated Gaussian noise but do exhibit some persistence.

Future Work

The present analysis can be extended simply by looking at more data. Extending the sample size would improve our knowledge of any differences in the pre- and post-flare distributions of the Hurst exponent. A study in which the Hurst exponent is measured in a sliding window leading up to a flare would be useful in the attempt to find detectable flare pre-cursors in LYRA data. Further, categorizing these measurements by flare size would give an indication of a correlation between flare size and persistence.

Much computational infrastructure has been created that can be used in the analysis of LYRA data in the future. In particular, the splitting of LYRA data into flaring and non-flaring time-series based on HEK results is very useful. For example, having split the original observational time-series into flaring and non-flaring time-series, it would be very simple to run a wavelet-based search and identification of quasi-periodic pulsations (QPPs; Foullon et al. 2005) in flaring plasma and compile an automatically generated survey of QPPs as observed by LYRA.

Acknowledgments
The author would like to thank the PROBA2 team and the Royal Observatory of Belgium for their help and support of this work.

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