Machine learning for autonomous on-board data processing

A prototype autonomy module for the STIX x-ray space telescope on-board Solar Orbiter

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INTRODUCTION

Solar flares occur in the Sun's heliosphere. They release huge amounts of energy, triggering many coronal mass ejections that travel down to earth and can be a hazard for our space infrastructure and astronauts. STIX observes solar flares from 4 keV to 150 keV in 32 energy bands and with a time resolution of up to 0.1s. On-board STIX, the raw measurements are aggregated in a pre-processing step that transforms the detected photon events into a very limited set of Fourier components of the desired image. Those components are then sent to ground for the final image reconstruction (figure 1). The process of transforming the raw measurements to Fourier components is configurable, depends on the scientific objectives and has an immense impact on the image quality.

For the planned mission operational phase, a conservative approach is implemented for data selection and pre-processing. The raw data is persisted in a high resolution (figure 2) on-board in a limited data memory and is only downloaded after a decision was taken on the ground. For a science team to decide on the best time-energy intervals on ground, regularly downlinked low-latency quicklook data in a very coarse resolution (figure 2 right) must be analyzed first.

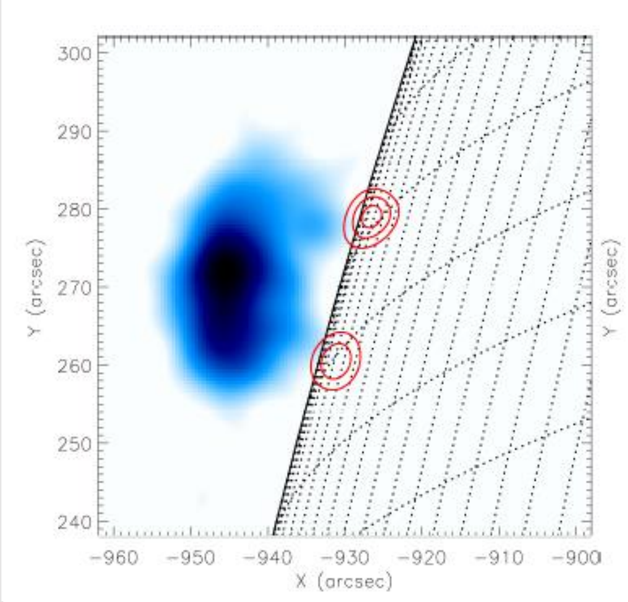

Figure 1:

A reconstructed simulated flare as seen by STIX, with the low energy component in blue, and the high energy foot points in red.

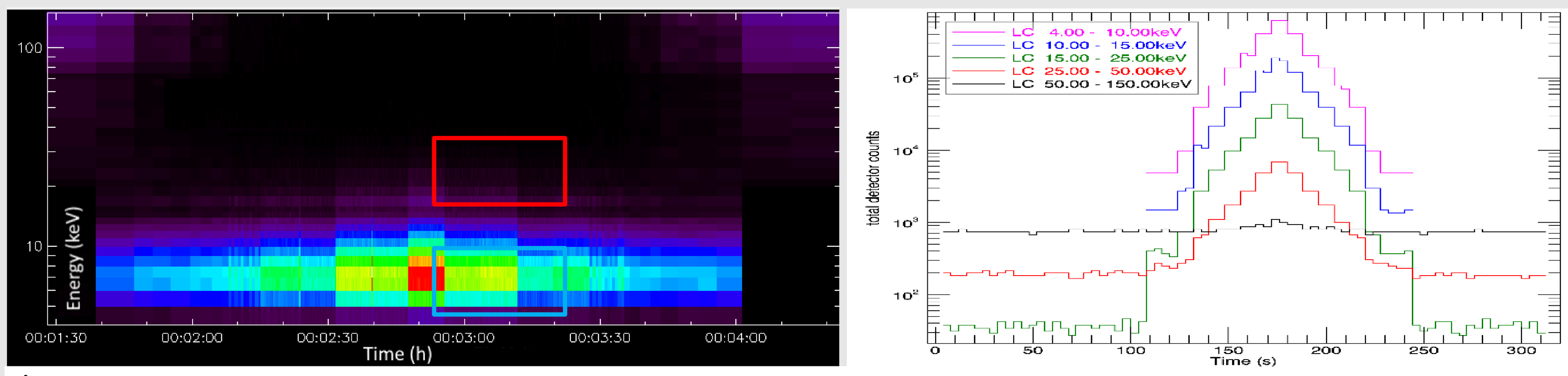

Figure 2:

(left) The measured high-resolution raw data of a flare as stored on board. (right) The same flare in the coarse time-energy resolution in the quicklook data available on ground.

Data from the red and blue time-energy intervals are transformed to reconstruct the original event as shown in figure 1.

OBJECTIVES

Space science missions suffer from bandwidth limitations when far away from earth or contacts to ground are sparse. The spacecraft and the ground software need to decide what data must be kept on-board and what data can be downloaded to ground. This implies a trade-off between telemetry rates versus more physical on-board memory – both posing their own technical, operational and financial challenges. The traditional approach to alleviate this issue is to involve humans: First, quicklook data are downloaded to ground, then a science team manually analyzes the data, and finally a decision is made on what precise data to request from the spacecraft.

This traditional approach is generally robust. However, with low telemetry rates, the quicklook data are lossily compressed before they are sent to ground for analysis. This means that the science team on the ground, which must do the analysis and take the decisions, may not obtain the data quality needed to make the best decision for a follow-up request for fully resolved data. This can result in wasting the already limited bandwidth by requesting the wrong data, in wasting storage space in the on-board memory, or, in the worst case, in overlooking or loosing valuable payload as the data are never selected and downloaded to ground. This approach inherently leads to a higher turn-around time, i.e. the time it takes until the desired data are available to the science community.

Our project technical objectives are to provide a module that can take decisions autonomously, without human intervention. We propose to rely on new machine learning techniques to find optimal parameter sets to configure the on-board autonomy module. This eliminates the need for ground-controlled intervention altogether. The on-board module has access to all the observed data and live context information and can therefore optimally configure the data processing and make an optimal decision on what products to send back to ground. These are not easy decisions to make and require a constant optimization of a variety of processing and selection parameters.

IMPLEMENTATION

Together with the STIX science team, we developed an on-board autonomous interval selection algorithm (aIVS) that finds optimal time-energy intervals to be send to the ground for image reconstruction. In order to make good decisions for the variety of all types of solar flares the aIVS has a very large parameter space of around 1800 variables. This crucial parameter set was optimized and trained with heuristic search strategies on a set of simulated flares and images. The algorithm was implemented and tested on a fully equivalent engineering model of the real instrument to ensure the results would be suitable for the Solar Orbiter space mission. We have been able to deal with the computational restrictions of the flight hard- and software and the performance of the algorithm is suitable for the mission science and operational objectives.

For verification we compared the results of the aIVS with two default schemata for the original ground-based data selection. Both generating regular grids of time-energy intervals: one fine (IVS: fine) and the other coarse (IVS: coarse). For all three tests, telemetry data was generated on the instrument and transmitted for analyses and image reconstruction. The results can be compared in figures 3 to 6.

RESULTS

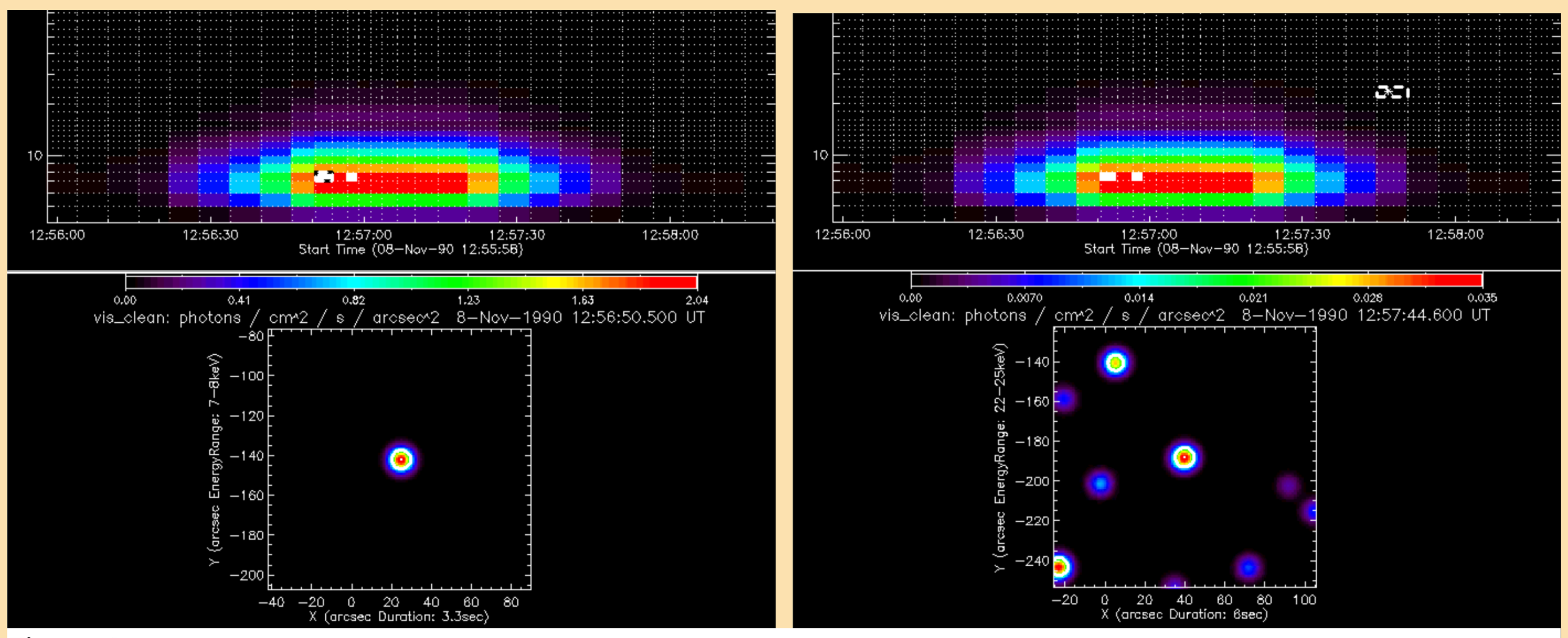

Figure 3:

Left: **IVS: fine** at energy-time: **low** → **very good** reconstruction of the original point source

Right: **IVS: fine** at energy-time: **high** → **very bad** reconstruction of the original point source

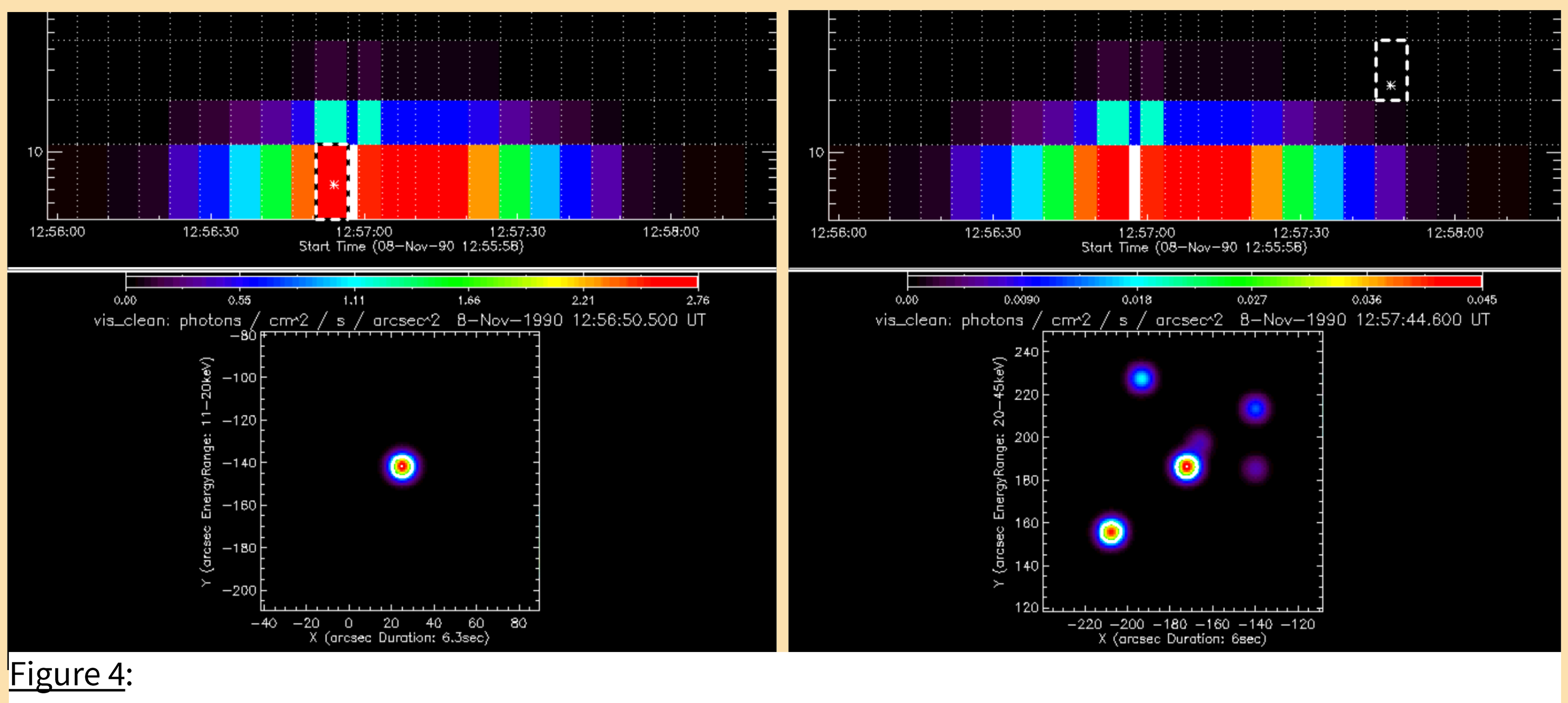

Figure 4:

(left) **IVS: coarse** at energy-time: **low** → **very good** reconstruction of the original point source

(right) **IVS: coarse** at energy-time: **high** → **bad** reconstruction of the original point source

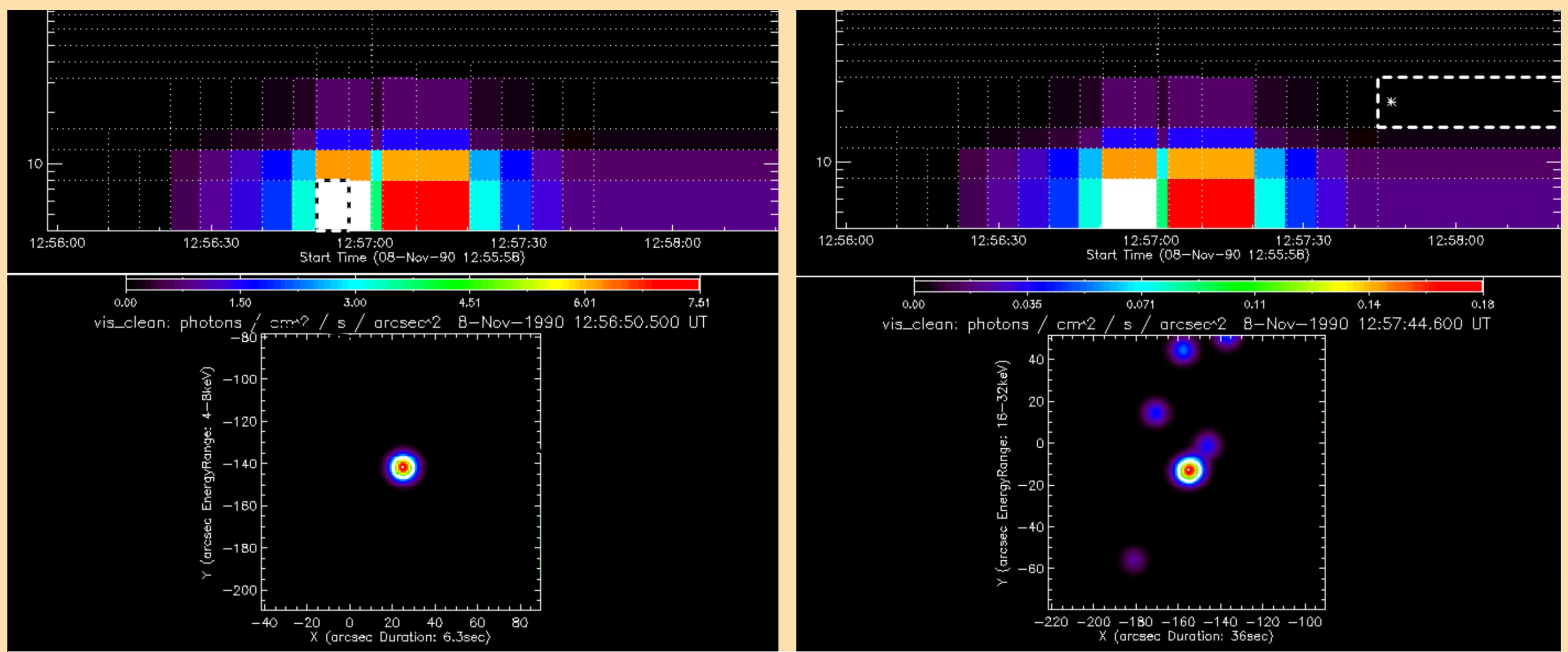

Figure 5:

(left) **aIVS** at energy-time: **low** → **good** reconstruction of the original point source

(left) **aIVS** at energy-time: **high** → **very good** reconstruction of the original point source

Algorithm		TM size / %	Total images	Good images	Ratio good-to-total
IVS: fine	Fig. 3	349kB / 100	896	214	23%
IVS: coarse	Fig. 4	51kB / 15%	130	53	40%
aIVS	Fig. 5	36kB / 10%	86	66	77%

Figure 6:

This sample case demonstrates that the telemetry data volume was reduced by the autonomous interval selection by a factor of 10 (349kB to 36 kB), while the percentage of good images was increased from 23% to 77%, without ground intervention.

The autonomous interval selection algorithm – a simple on-board AI – shows the potential of machine learning and optimization techniques to

- **improve space instrument data quality** while
- **reducing telemetry budget demands**, and
- **eliminating the need for ground intervention**, and
- **greatly reducing the turn-around time** for receiving good observation data or events.

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solar orbiter

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