Automated detection and tracking of CMEs using HI instruments

Maike Bauer[a,b], Justin Le Louëdec[a], Tanja Amerstorfer[a], Jackie Davies[c]
a) Austrian Space Weather Office, GeoSphere Austria, Graz, Austria
b) Institute of Physics, University of Graz, Graz, Austria
c) RAL Space, Science and Technology Facilities Council, Didcot, UK

FWF Österreichischer Wissenschaftsfonds

GeoSphere Austria

Abstract

The capability to predict the arrival of **coronal mass ejections (CMEs)** in real-time is crucial in mitigating the potential impact of severe space weather events. Detection and tracking of CMEs as they traverse the heliosphere is currently done mostly manually. Our objective is to implement an algorithm for **automatic detection and tracking** that can effectively utilize data from various **heliospheric imager (HI) instruments.** We present preliminary outcomes from an automated CME detection and tracking algorithm trained on STEREO-HI data.

1. Data & Methods

We use **5140 STEREO-A HI science images** from January to May of 2010. We apply standard pre-processing and create running difference images to enhance CME visibility.

We annotate the outermost part of the CME and split the dataset into a training, test, and validation set with ratios 70/20/10. To avoid data leakage, one CME is always assigned to a set in its entirety. Data augmentation is performed to avoid overfitting.

The model:

- **U-Net[1]** – 3D neural network with a distinctive U-shaped architecture featuring identical up- and downsampling paths
- Sequences of 16 images, with stride of 2
- Binary Cross-Entropy (BCE) Loss
- Run for 100 epochs, optimized via Adam algorithm and plateau scheduler with an initial learning rate of 1e-5

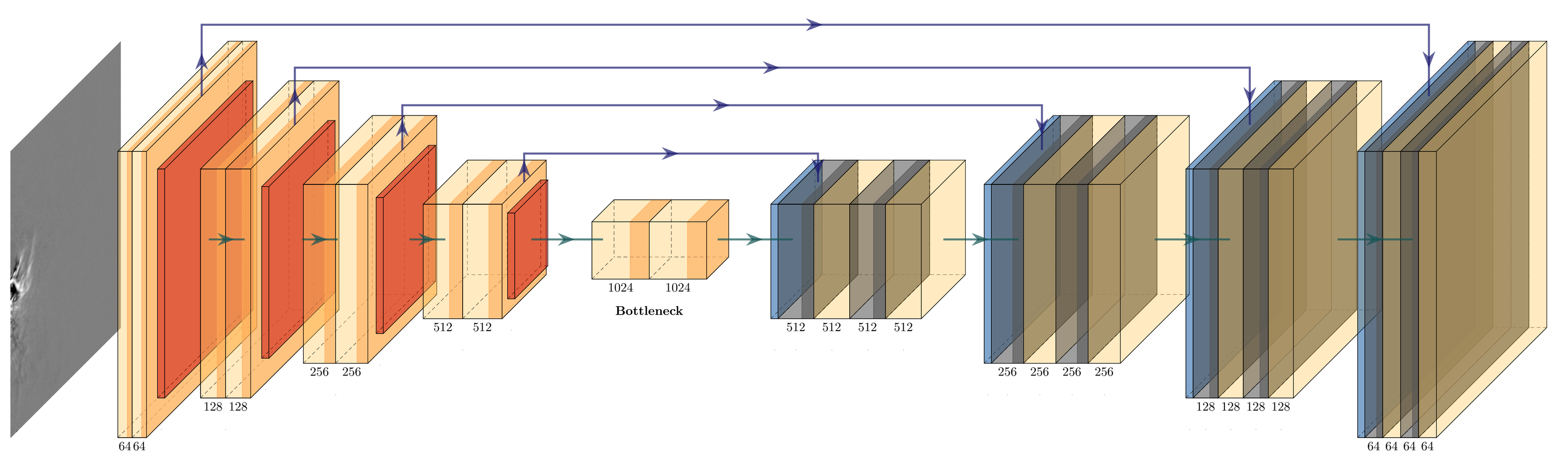

Fig. 1: Schematic depiction of U-Net architecture.

2. Results

- Identifying fronts is subjective and poses a challenge to humans (incomplete annotations, missed CMEs, etc.)
- The front is detected, but under-segmented compared to the ground truth
- Rate of false positive detections is low, some false positives might be incorrectly labeled
- Improving post-processing of segmentation masks will further improve performance
- Annotating more CME events will improve model's ability to generalize

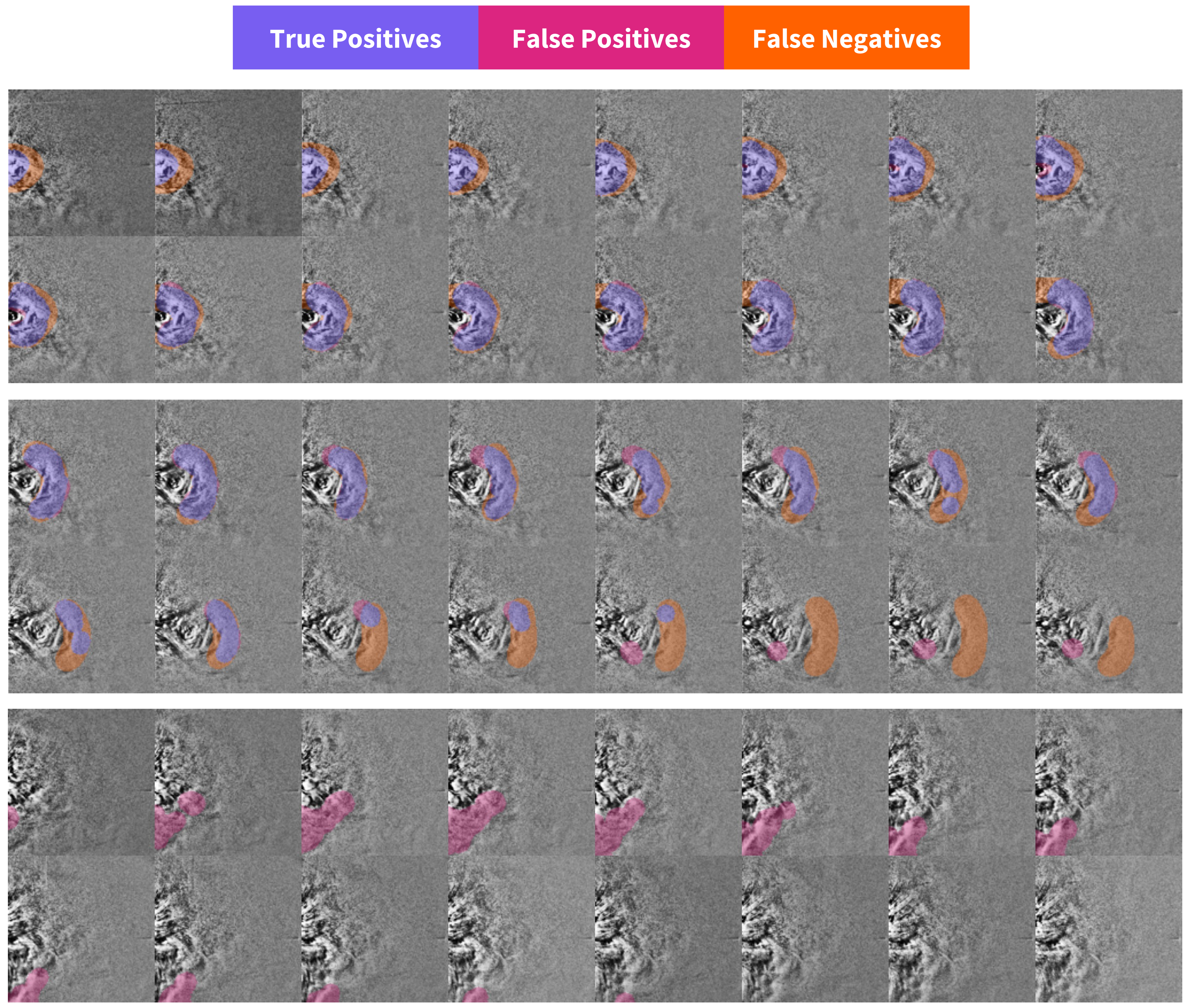

Fig. 2: Results of segmentation performed on test dataset. The top row shows promising results for the early phase of CME propagation, while the middle row highlights the model's issues with tracking CMEs as they become fainter. The bottom panel shows a possible CME detected by the model which was not annotated, and is thus classified as a false positive.

$$\text{IOU} = \frac{TP}{TP + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

IOU	0.39
Precision	0.60
Recall	0.55

Tab. 1: Intersection-over-Union (IOU), precision, and recall for segmentation performed on the test dataset.

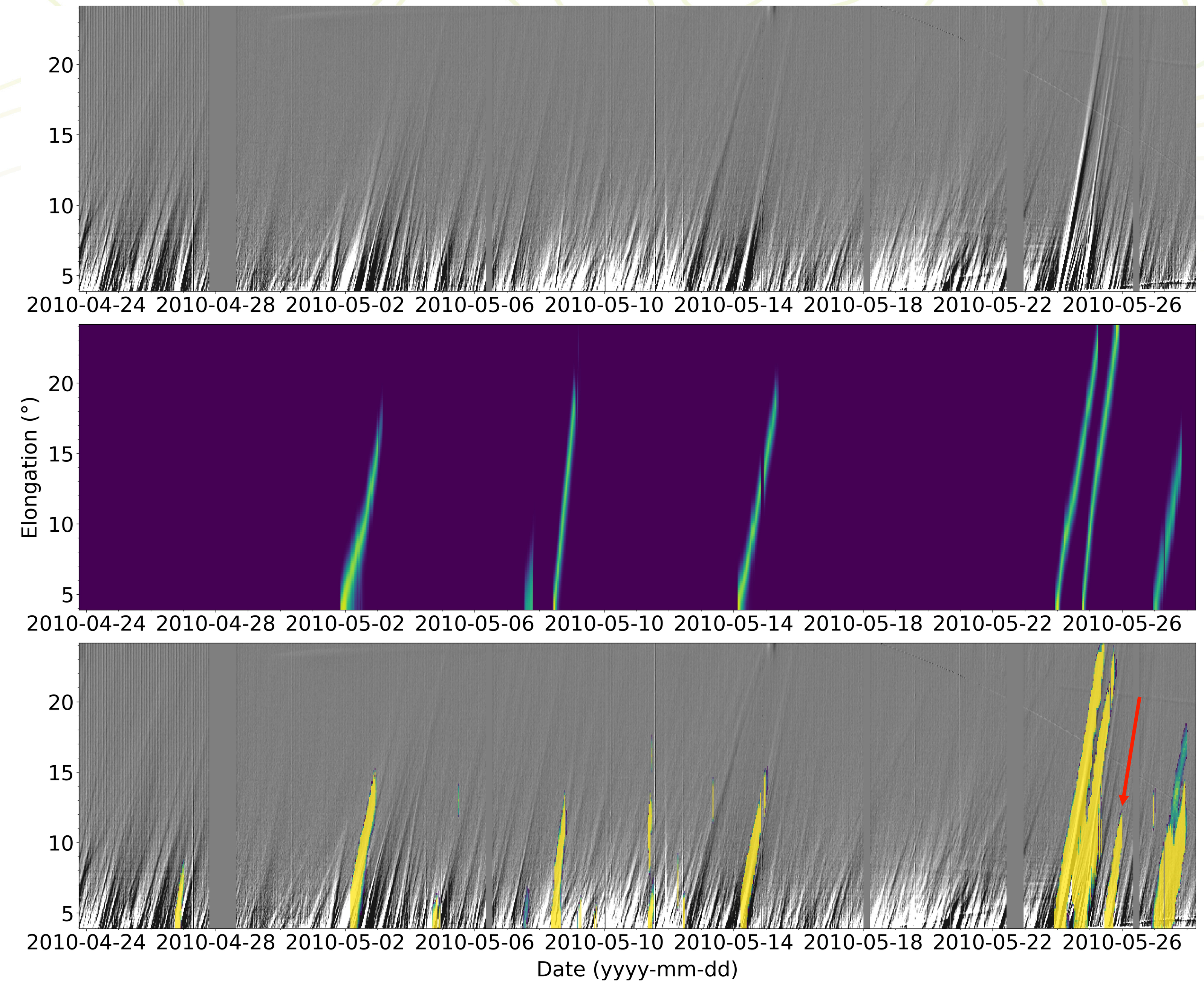

Fig. 3: Comparison between real, ground truth, and predicted ecliptic J-Map. The top panel shows the real J-Map for the length of the test dataset.The middle panel shows the J-Map made using the ground truth masks. The bottom planel displays the output mask overlaid onto the real J-Map – the red arrow points out a false positive event that has possibly been overlooked during annotation.

3. Summary

- We use a Res-U-Net to perform semantic segmentation on HI observations to automatically detect and track CMEs
- Using sequences as input improves performance, ensures temporal consistency
- Additional data, post-processing of segmentation masks will help improve performance further
- Model might be able to help with detecting CMEs that are less prominent and thus not immediately obvious

References

- [1] O. Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

This research was funded in whole, or in part, by the Austrian Science Fund (FWF) P 36093.

Contact: Maike Bauer, Austrian Space Weather Office | maike.bauer@geosphere.at | www.geosphere.at