Advanced Image Preprocessing and Feature Tracking for Remote CME Characterization with Deep Learning

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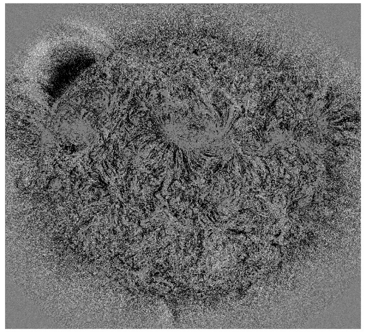
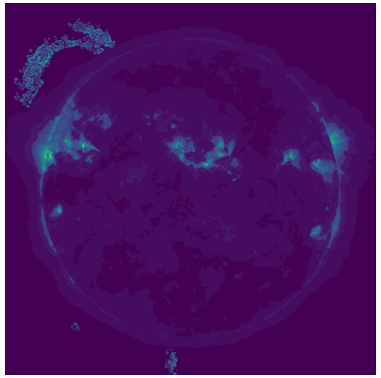


Base Difference



Feature Mask (RAW projected)

Background, Motivation

Coronal Mass Ejections (CMEs) influence the interplanetary environment over vast distances in the solar system by injecting huge clouds of fast solar plasma and energetic particles (SEPs). A number of fundamental questions remain about how SEPs are produced, but current understanding points to CME-driven shocks and compressions in the solar corona. At the same time, unprecedented remote (AIA, LOFAR, MWA) and in situ (Parker Solar Probe, Solar Orbiter) solar observations are becoming available to constrain existing theories. A major goal of the MOSAIICS project under the VIHREN programme is to develop and integrate novel techniques to reliably analyze radio and EUV remote imaging observations of CMEs and their shocks.

Challenges

- Reliable CNN training sets are still missing (“Catch 22 problem”)
- General complexity of algorithmic approach for such class of tasks
- Multiple events processing
- Dynamic range of the images
- Various data sources (AIA, kcor), different channels and calibration

Here we present hybrid algorithmic-data driven method for detecting and tracking various solar and heliospheric phenomena in imaging observations.

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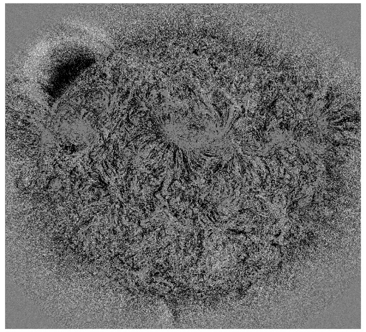

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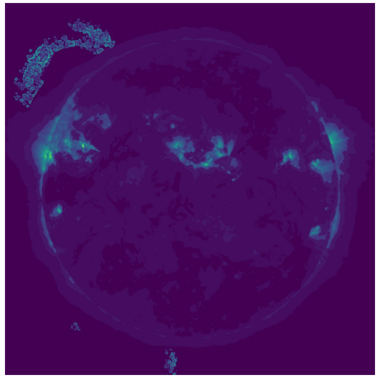

Feature Mask (RAW projected)

What do we do ?

- We designed a Wavetrack - a generalized object-oriented framework for solar
- feature detection
- Every object class represents one or a few image processing techniques,
- Classes act as "building blocks" allowing various decomposition and processing setups, depending on the input image characteristics.
- We use Wavetrack to create CNN training sets
- Adopt U-Net for Solar Eruptive Feature Extraction and Characterization. U-Net is a convolutional neural network that was developed for biomedical image segmentation at the Computer Science Department of the University of Freiburg. We showcase it's performance on test dataset from the few events processed by Wavetrack.

Here we present hybrid algorithmic-data driven method for detecting and tracking various solar and heliospheric phenomena in imaging observations.

Solar Eruptive Feature Extraction and Characterization: algorithmic approach

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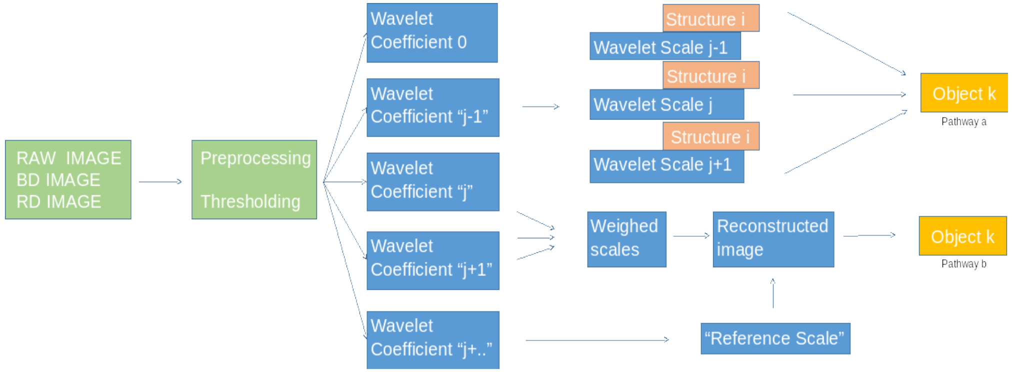
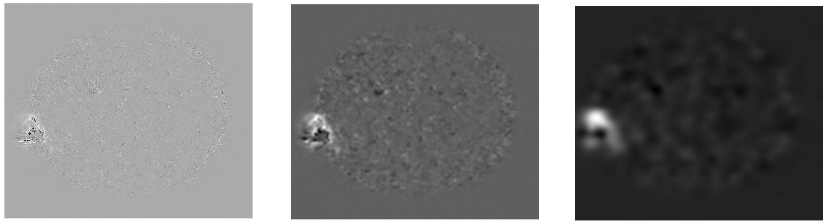
- Pre-processing techniques: thresholding, normalization, posterization, median-filtering
- Decomposition: A-trous Wavelet, Intensities
- Objects recognition: wavelet multiscale
- Objects separation: saddle points (gradient), clustering, “abc-mask”

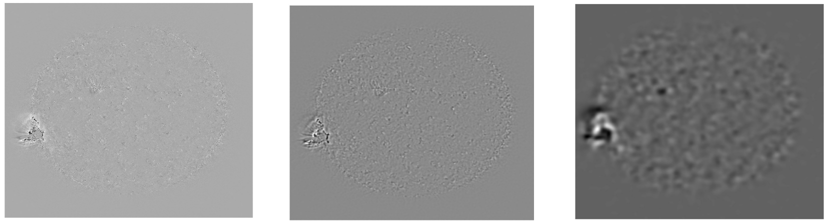
Image Processing stages with Wavetrack software



A Trous wavelet decomposition

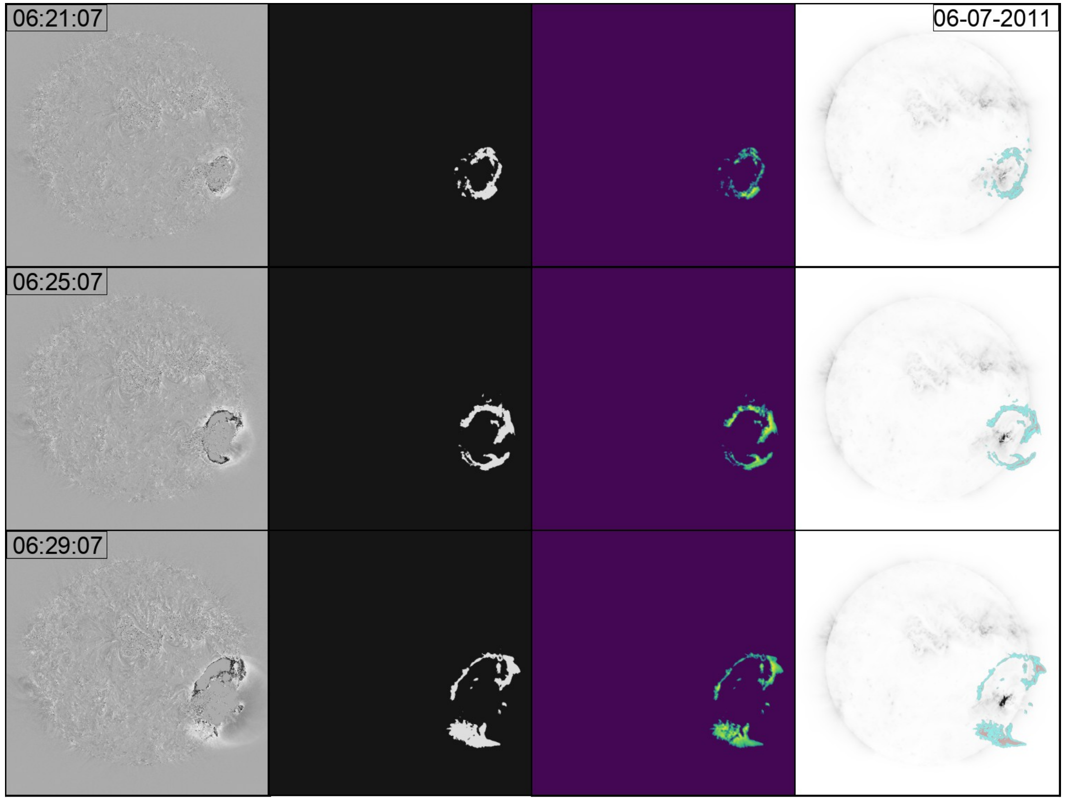


Base Difference | Wavelet coeff 2 | Wavelet coeff 5



Base Difference | Wavelet Scale 2 | Wavelet Scale 5

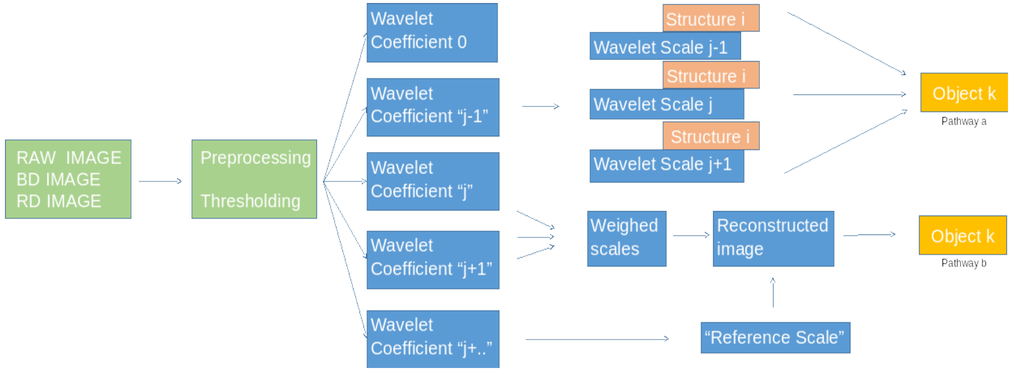
The shock wave: Demonstration of the Wavetrack application stages four times during the event of June 07, 2011 (Stepanyuk et. al. J. Space Weather and Space Climate (under review))



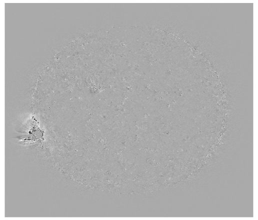
Base Difference | Feature Mask | Feature Mask (RAW data) | Feature Mask (RAW projected)

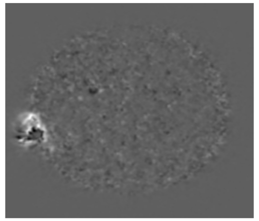
Solar Eruptive Feature Extraction and Characterization: algorithmic approach

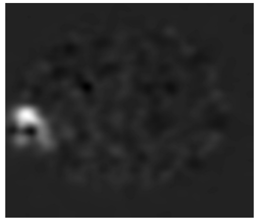
Image Processing stages with Wavetrack software

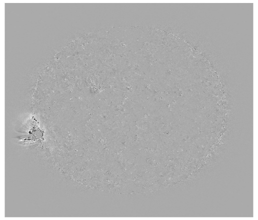


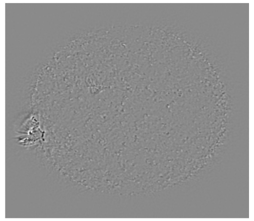
à trous wavelet decomposition

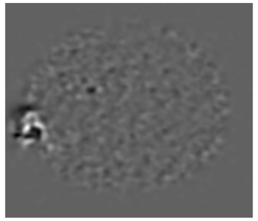

Base Difference


Wavelet coeff 2


Wavelet coeff 5


Base Difference


Wavelet Scale 2


Wavelet Scale 5

Basic Idea: Hilbert space decomposition as a subset of orthogonal subspaces (with corresponding scaling functions):

$$V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2} \subset \ldots, \bigcap_{m \in Z} V_m = \{0\}, \bigcup_{m \in Z} = L^2(R)$$

Image decomposition as:

$$I(x,y) = \sum_{i=1}^{n} O_i(x,y) + F(x,y) + B(x,y)$$

(Objects (O), background(F) and noize (B))

Structures by definition:

$$S_{j,k} = \{w_j[k_1, l_1], w_j[k_2, l_2], \ldots, w_j[k_p, l_p]\}$$

Objects by definition:

$$O_l = \{S_{j_1,k_1}, \ldots, S_{j_n,k_n}\}$$

Object condition for a structure:

$$w_j^m > w_{j-1}^m \quad w_j^m > w_{j+1}^m$$

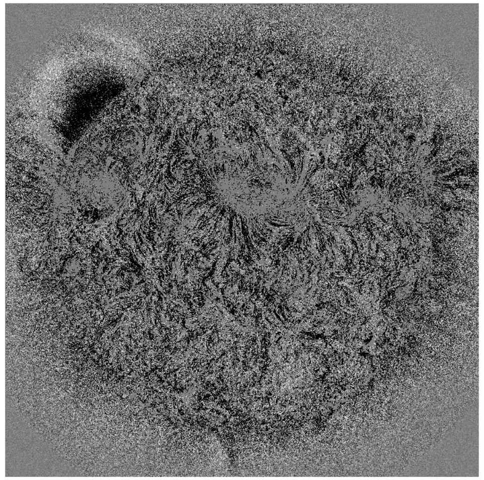
Where:

$$w_{j+1}^m = max\{w_{j+1,x_1,y_1}, \ldots, w_{j+1,x_n,y_n}\};$$

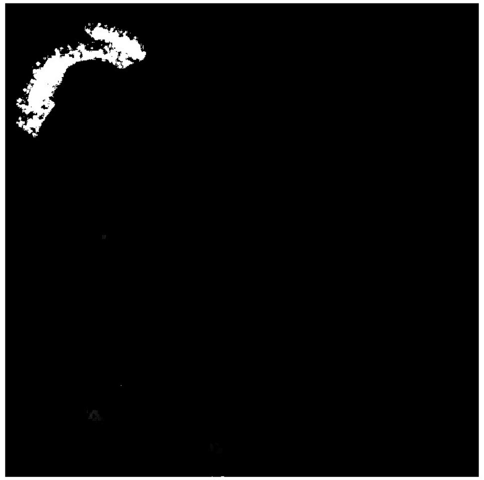
$$w_{j,x,y} \in S_{j,k}$$

** See later. *JL. Starck, Handbook of Astronomical Data Analysis - 2002

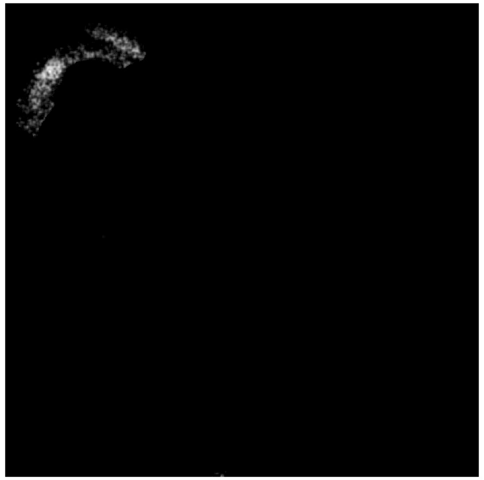
The shock wave recognition: a single timestep



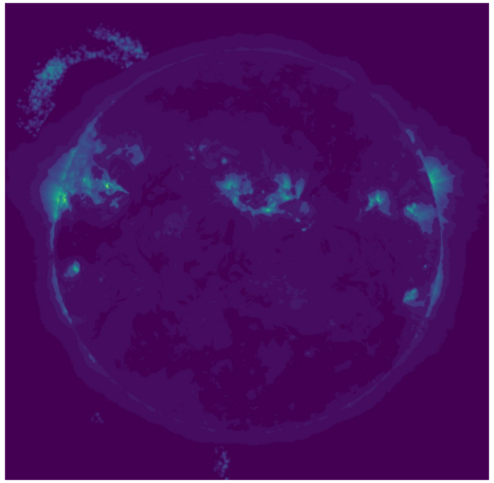
Base Difference



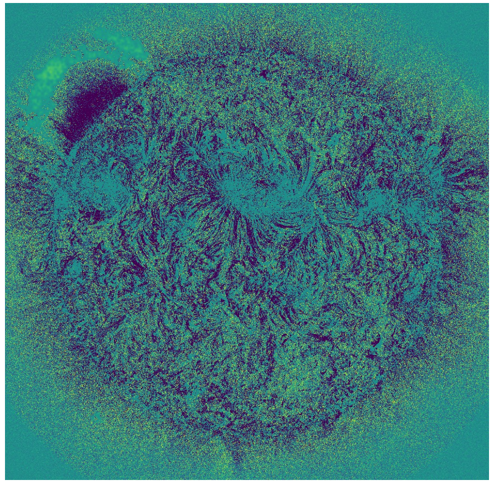
Object Mask



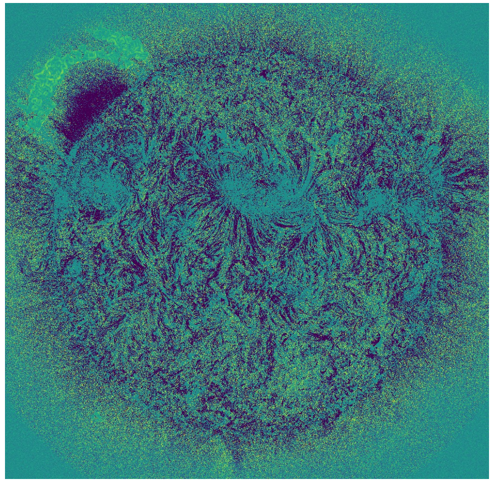
Mask applied to the RAW Data



Mask Filtered Image projection



Mask Base Difference projection



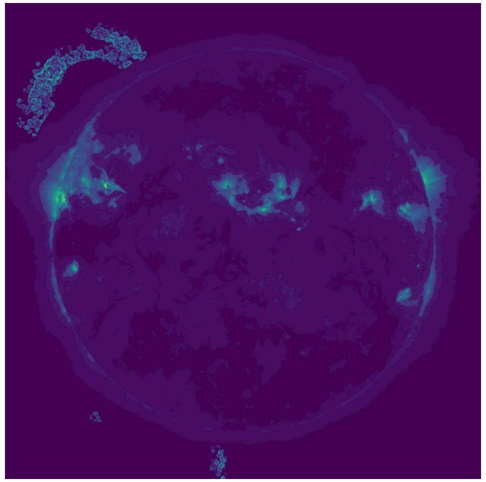
Mask Gradient Base Difference projection

Contours and saddle points (zero gradient fields): Sobel-Feldman Operator :

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

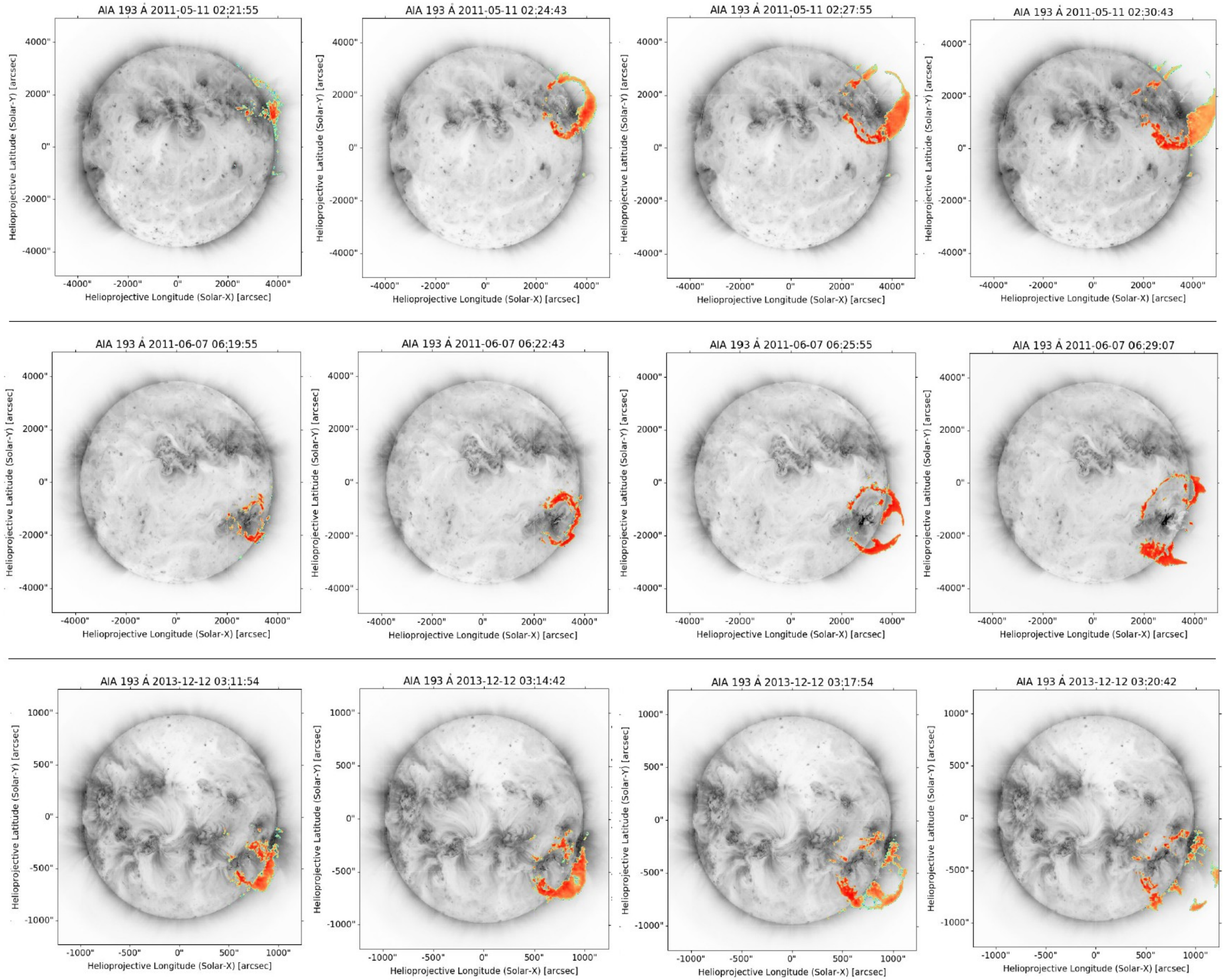
$$\mathbf{G} = \sqrt{{\mathbf{G}_x}^2 + {\mathbf{G}_y}^2} \qquad \mathbf{\Theta} = \operatorname{atan}\left(\frac{\mathbf{G}_y}{\mathbf{G}_x}\right)$$

***Alternatively: Curvature method Hagenaer et. al. Astr.J. 511:932-944, (1999)



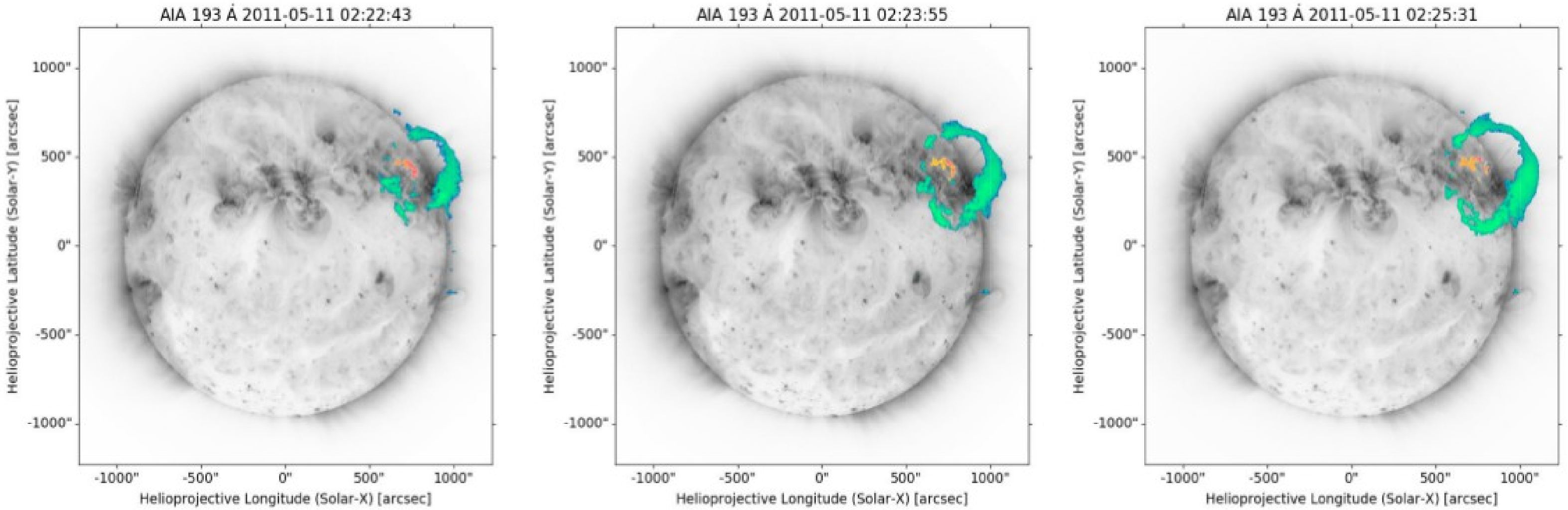
Gradient Mask Filtered Image projection

CBF: May 11, 2011; June 07,2011; December 12, 2013



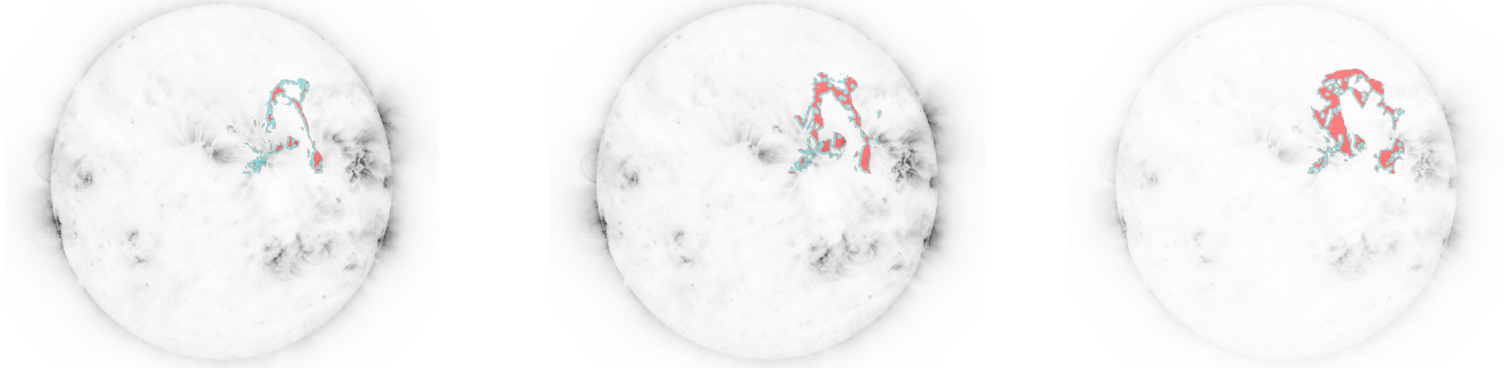
(Stepanyuk et. al. J. Space Weather and Space Climate (under review))

Shock wave and a filament separate recognition



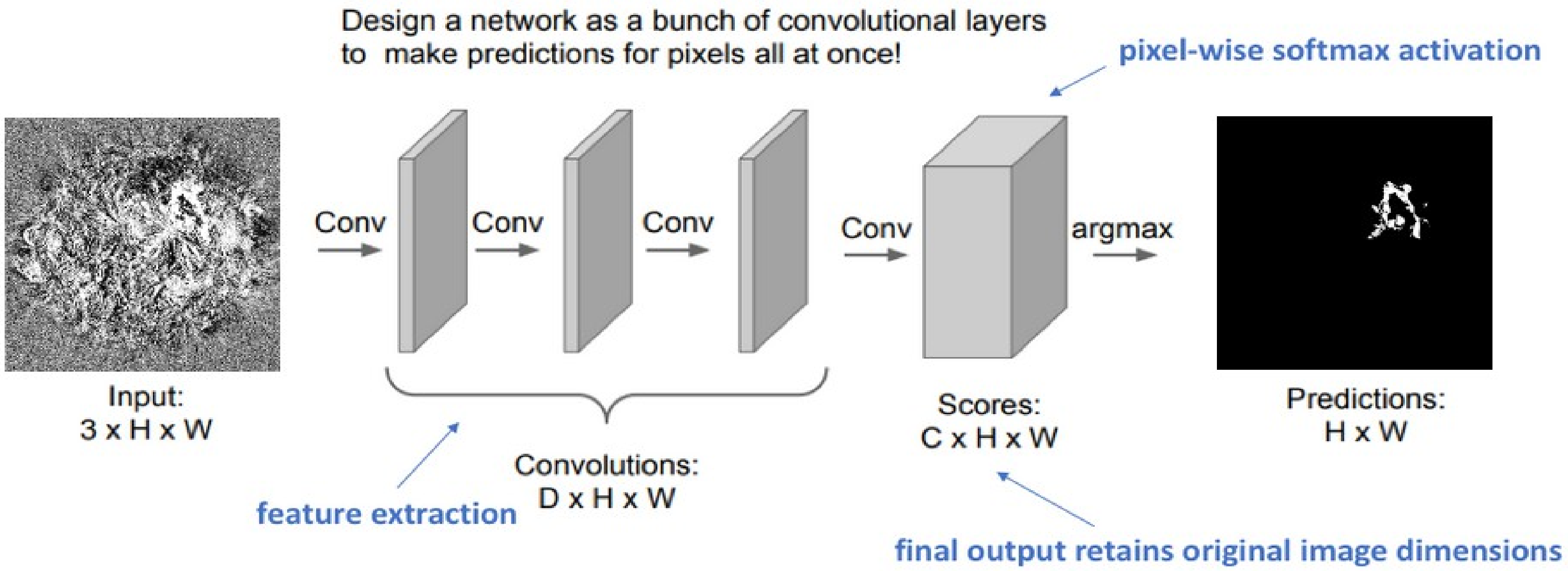
CBF and the filament: Combined tracking of the May 11, 2011 event

AIA193: 21:31:06 AIA193: 21:39:54 AIA193: 21:49:06



Gigantic filament: Tracking of the September 29, 2013 event

(Stepanyuk et. al. J. Space Weather and Space Climate (under review))


Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!
pixel-wise softmax activation
Conv
Conv
Conv
Conv
argmax
Input:
3 x H x W
Scores:
C x H x W
Predictions:
H x W
feature extraction
Convolutions:
D x H x W
final output retains original image dimensions

Versus

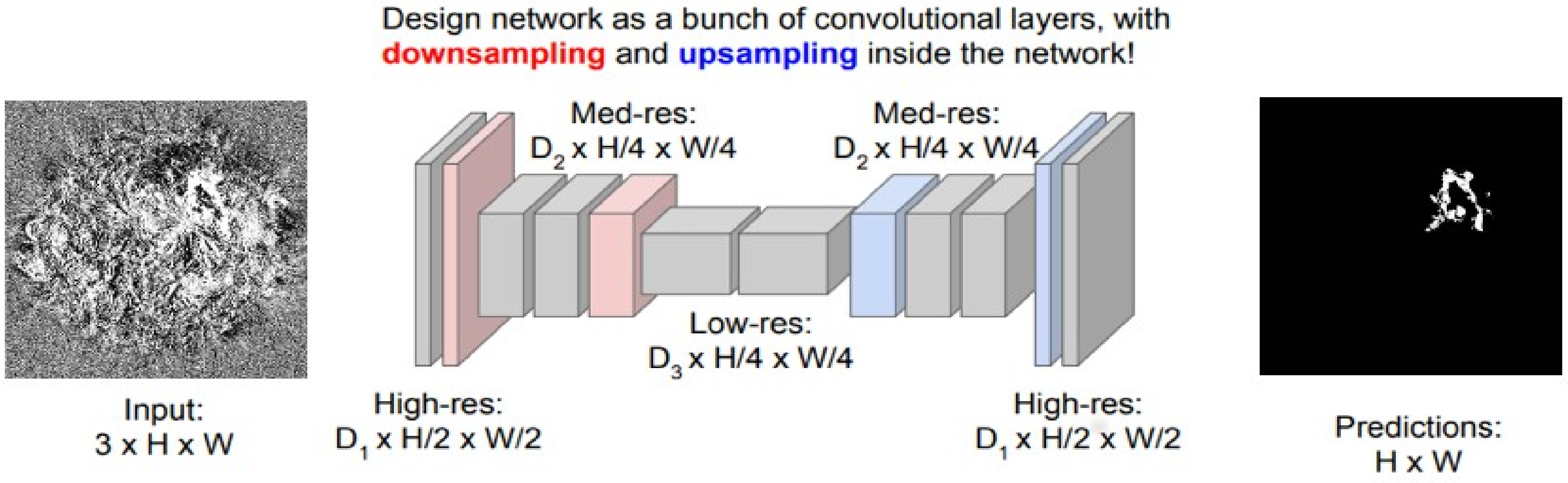
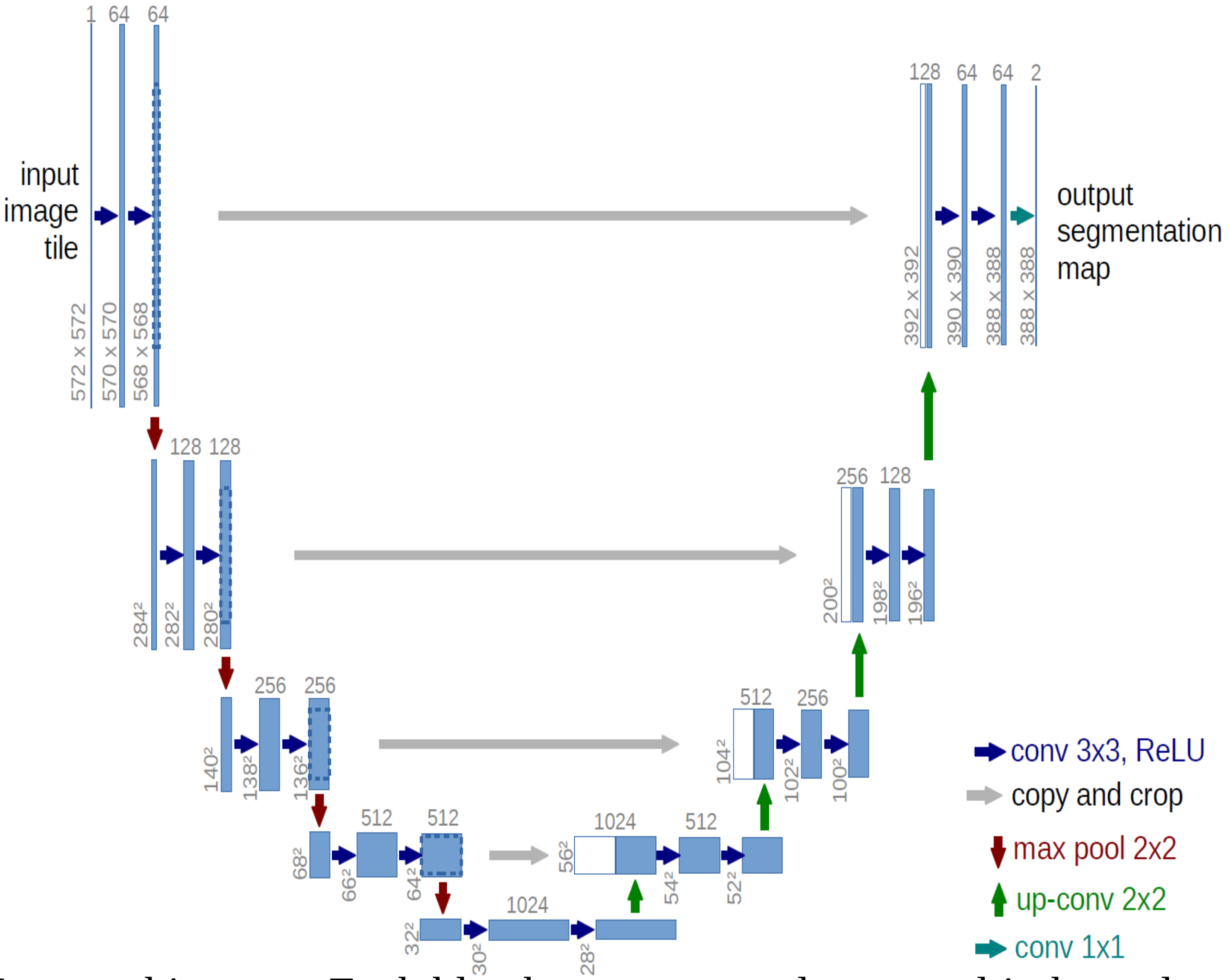
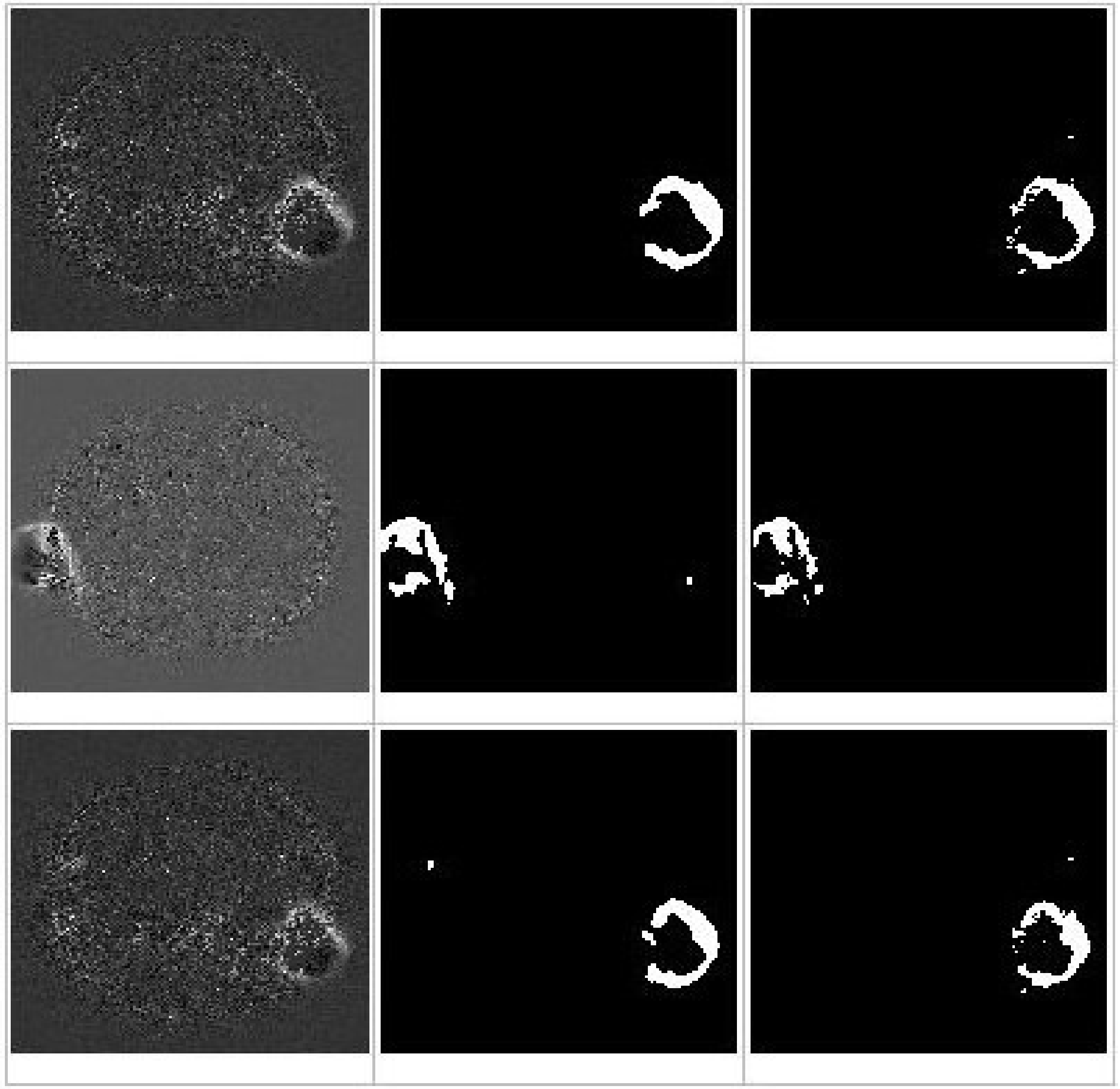

Design network as a bunch of convolutional layers, with
downsampling and upsampling inside the network!
Med-res:
D_2 x H/4 x W/4
Med-res:
D_2 x H/4 x W/4
Low-res:
D_3 x H/4 x W/4
Input:
3 x H x W
High-res:
D_1 x H/2 x W/2
High-res:
D_1 x H/2 x W/2
Predictions:
H x W

Image Segmentation with CNN.U-Net



U-net architecture. Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps.



Base Difference | U-Net produced mask (Validation set) | Control Mask (Wavetrack)

Ronneberger O, et. al (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation". ArXiv:1505.0459

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Conclusions

- We designed a Wavetrack - a generalized object-oriented framework for solar feature detection
- Every object class represents one or a few image processing techniques
- Classes act as "building blocks" allowing various decomposition and processing setups, depending on the input image characteristics.
- We use Wavetrack to create CNN training sets to switch from algorithmic to data-driven approaches
- We propose to adopt U-Net for Solar Eruptive Feature Extraction and Characterization. U-Net is a convolutional neural network that was developed for biomedical image segmentation at the Computer Science Department of the University of Freiburg. We showcase it's performance on test dataset from the few events processed by Wavetrack.