

## CORONAL MASS EJECTION IMAGE EDGE DETECTION IN HELIOSPHERIC IMAGER STEREO SECCHI DATA

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## ABSTRACT

We present an algorithm to detect the outer edges of Coronal Mass Ejection (CME) events as seen in differences of Heliospheric Imager STEREO SECCHI HI-1 images from either A or B spacecraft, as well as its implementation in Python.

## 1. INTRODUCTION

Studying and monitoring Sun's activity, and in particular, its stronger radiation and particle emission abrupt events, is important for both science and practical purpose, for our life on and around Earth. In particular, Coronal Mass Ejections (CME), which energetically carry away accelerated charged particles, can create electromagnetic storms on our planet, and also endanger astronauts or space equipment. Increased interest in studying their origins, structure, and trajectories resulted in more and more international space missions, among which several ones are still operational. The STEREO pair A and B of NASA spacecraft is one of such latest missions, continuously imaging the Sun and the space between Sun and Earth, with several instruments, as described in Eyles et al. (2009); Eyles et al. (2007) by orbiting around the Sun at roughly the same distance as the Earth<sup>1</sup>. Two visible-light cameras HI-1 and HI-2 on each spacecraft are thus precisely aimed in order to cover the line Sun-Earth, while being shielded from the Sun itself. Their images show various parts of Sun's corona, receiving free-electron scattered light from the K-corona, dust scattered light from the F-corona, as well as light from background stars. Many studies of these images start from running differences, as described by Sheeley et al. (1997) for coronagraph images, to enhance the faint K-corona light and remove the slowly-varying but much stronger F-corona light, as also explained in Davies et al. (2009). CME perturb the K-corona, and thus appear as bright regions in these images. Successive images, obtained from space missions such as the SOHO LASCO Yashiro et al. (2004), and STEREO coronagraph and HI cameras, show their propagation and evolution. Considerable research studying the CME origin mechanisms, shape, and trajectories is in progress, but open problems remain, as described in the very comprehensive review from Webb & Howard (2012), in particular regarding propelling forces and interaction with solar wind: such models can be found in Xie et al. (2006); Michalek et al. (2006); Gopalswamy & Yashiro (2007); Howard et al. (2008). Given the large amount of data as well as the need for tracking, computerized pre-analysis tools can provide important help, in particular to identify the CME boundaries and kinematics.

Generally speaking, many computer vision techniques for edge detection have been devised, such as the ones based on gradient, e.g the Canny algorithm Canny (1986), as well as the family of active contours Caselles et al. (1993); Chan & Vese (2001); Márquez-Neila et al. (2014). However, as Young &

Gallagher (2008) explain, it is not straightforward to use existing techniques because of the diffuse nature of CMEs. Moreover, they also have complex inner features, and their images appear next to light from many background stars, which adds to the noise.

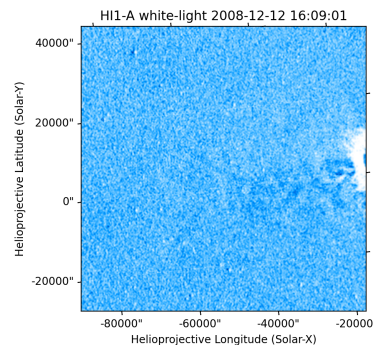
Thus, several complex algorithmic methods specialized for this task have been devised: CACTus Robbrecht & Berghmans (2004), SEEDS Olmedo et al. (2008), and multiscale wavelet analysis Young & Gallagher (2008); Byrne et al. (2009), mainly focused on the coronagraph images. These methods isolate the regions of interest in specific ways, and then estimate geometric and kinematic parameters, using underlying assumptions such as constant acceleration and elliptical shapes.

The algorithm presented here only focuses on the image segmentation stage, identifying the outer edge of CME regions in STEREO HI images using a staged approach composed of simple steps. The algorithm starts by filtering and smoothing the image difference, subsequently exploring it from the center of the bright CME region, marking its outer edges.

Through subsequent work, it can be integrated into various kinematic estimation schemes. Given its modular nature, the algorithm itself could also be further adapted to examine specific internal features apparent in the images.

The rest of the paper is organized as follows. In Section 2 we describe the algorithm outline and its subsequent processing of an image. In Section 3 we show its results on several other STEREO HI-1 images of known CME, and in Section 4 we discuss future lines of work.

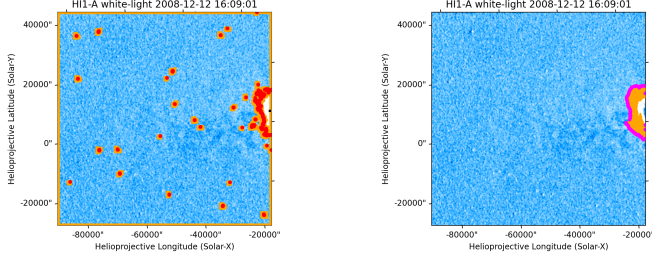
## 2. ALGORITHM



**Figure 1.** Background-removed 0-to-255 normalized diff image from STEREO HI-1 Spacecraft A, used as input

<sup>1</sup> Currently only STEREO-A is operational, but several years of raw and processed image data are available from both.

In Figure 1 we see an example of what the algorithm starts with, which is an early phase of a CME visible in the differenced image from December 12, 2008. The Sun is behind the right edge of the image, which has  $n_c \times n_r = 1024 \times 1024$  pixels.



**Figure 2.** Intermediate processing stages

The main steps, graphically illustrated in Figure 2, are as follows, where  $I[c, r]$  represents the pixel intensity for coordinates column  $c$  and row  $r$  of the input image. The origin is the bottom left of the image.

1. Find the center of mass  $(x_S, y_S)$  of the bright area and set  $C = (c_S, y_S)$  where  $c_S$  is close to the image edge  $c_0$  towards the Sun (right for spacecraft A, so typically  $c_0 = 1023$ , and left for B, i.e.  $c_0 = 0$ ).

2. Going from  $c_S$  to  $c_E$  (1023 for B, 0 for A), on each image row  $r$ , mark the farthest bright pixels seen along. Then do the same on each image column  $c$ , first from  $y_S$  up, and then from  $y_S$  down, with  $t_1 = 240$  for 0-255 gray level images.

```

1:  $e_1 \leftarrow []$ 
2: for each image row  $r$  do
3:    $q \leftarrow \text{False}$ 
4:    $v \leftarrow c_0$ 
5:   for each image column  $c$  from  $c_S$  to  $c_E$  do
6:     if  $I[c, r] > t_1$  then
7:        $v \leftarrow c$ 
8:        $q \leftarrow \text{True}$ 
9:     end if
10:  end for
11:  if  $q$  then
12:     $e_1+ \leftarrow [v, r]$ 
13:  end if
14: end for
15: for each image column  $c$  do
16:   for each image row  $r$  from  $y_S$  to  $r_E$  do
17:     if  $I[c, r] > t_1$  then
18:        $v \leftarrow r$ 
19:        $q \leftarrow \text{True}$ 
20:     end if
21:   end for
22:   if  $q$  then
23:      $e_1+ \leftarrow [c, v]$ 
24:   end if
25:   for each image row  $r$  from  $y_S$  to 0 do
26:     if  $I[c, r] > t_1$  then
27:        $v \leftarrow r$ 
28:        $q \leftarrow \text{True}$ 
29:     end if

```

```

30:   end for
31:   if  $q$  then
32:      $e_1+ \leftarrow [c, v]$ 
33:   end if
34: end for

```

3. Smooth the image  $I$  into  $I_M$ , using a sum-scale-and-modulo-256 5x5 filter to enhance contrast at the edges

4. Mark the contrasting pixels created in step 3, with  $t_2 = 120$  for 0-255 gray level images

```

1:  $e_2 \leftarrow []$ 
2: for each image row  $r$  do
3:   for each image column  $c$  except the last one do
4:     if  $|I_M[c, r] - I_M[c + 1, r]| > t_2$  then
5:        $e_2+ \leftarrow [c, r]$ 
6:     end if
7:   end for
8: end for
9: for each image column  $c$  do
10:  for each image row  $r$  except the last one do
11:    if  $|I_M[c, r] - I_M[c, r + 1]| > t_2$  then
12:       $e_2+ \leftarrow [c, r]$ 
13:    end if
14:  end for
15: end for

```

5. Mark the centers where both kinds of previous marks are present in a  $w_i \times w_i$  window, as created in step 2 and step 4, namely from the  $e_1$  and  $e_2$  lists:

```

1:  $I_1 = \text{ones}[n_c, n_r]$ 
2:  $I_2 = \text{ones}[n_c, n_r]$ 
3: for each element  $[x, y]$  of  $e_1$  do
4:    $I_1[x, y] \leftarrow 2$ 
5: end for
6: for each element  $[x, y]$  of  $e_2$  do
7:    $I_2[x, y] \leftarrow 3$ 
8: end for
9:  $I_3 \leftarrow I_1 + I_2$ 
10:  $I_4 \leftarrow \text{filter}(I_3, \text{prod}, w_i)$ 
11:  $e_3 \leftarrow \text{list of } [x, y] \text{ such that } I_4[x, y] \text{ is a multiple of } 2 \text{ and } 3, \text{ or of } 5$ 

```

6. Estimate the density of the markers from step 5 in a larger window  $w_d \times w_d$  and mark those above half into a boolean mask  $I_D$ .

7. Circularly sweeping from the center, for each such radial half-line gather the last mark as created in step 6, i.e. from  $I_D$ , and build the perimeter:

```

1:  $e_4 \leftarrow []$ 
2: for each angle  $\alpha$  from 0 to  $2\pi$  in steps of  $\varepsilon$  do
3:    $v \leftarrow \text{Nothing}$ 
4:   for each pixel  $[x, y]$  along the  $\alpha$  ray from  $[c_S, y_S]$  to any edge of the image do
5:     if  $I_D[x, y]$  then
6:        $v \leftarrow [x, y]$ 
7:     end if
8:   end for
9:   if  $v$  then
10:     $e_4+ \leftarrow v$ 
11:   end if
12: end for

```

8. Remove spikes (outliers) created in step 7 in the list  $e_4$  of pairs of pixel coordinates, reconnect and validate the final perimeter, based on CME geometry from Fisher (1984); Fisher & Munro (1984); Crifo (1983).

The idea behind step 3 is to augment existing gradual contrasting zones by creating an abrupt transition through the modulo operation.

Given the larger density of markers around the true edge, even if the rays in step 7 are one or two pixels wide, they should not miss them when they cross it outwards.

Outliers appear occasionally because of brighter background light points far away from the CM, and can be removed in step 8. The validation of the perimeter, to eliminate unphysical results, is based on CME general geometry, using bubble and loop models as described in Crifo (1983). Specifically, as Fisher (1984) and Fisher (1984) point out, the width to depth ratio is typically 3:2, so we compute and compare these diameters.

### 3. RESULTS

We have tracked CME events using a set of 100 STEREO 11-day background-removed L2 HI-1 a and b images from the UK Solar System Data Center, <https://www.ukssdc.ac.uk>. The algorithm performed with overall high predictive abilities and without any fine-tuning or training set. We also conducted a manual identification of the CME regions, and then compared it with the automatic one. We counted the relative differences in areas between the two perimeters as errors, and we measured by hand that the percentage error of region identifications was below 15% for the most irregular events. We did not find false positives. The images in Figure 3 and Figure 5 illustrate these cases.

A simplified initial calculation appears in agreement with speeds of the order of 300km/s from Davis et al. (2009) for the 2008 December 12 CME event, as effectively measured by the SWEPAM instrument aboard the Advanced Composition Explorer spacecraft Stone et al. (1998). We used the transformation (4) described in Thompson (2006):

$$x \simeq D_{\odot} \left( \frac{\pi}{180^{\circ}} \right) \theta_x$$

to compute the displacement of the front, from the Helioprojective longitude displacement of  $\theta_x = 0.27^{\circ} = 1000$  seconds of arc from 18:09 to 18:49 of two algorithm-generated contours for HI-1 B, shown in Figure 4. Thus,  $\Delta x = 730000\text{km}$ , and  $\Delta t = 2400\text{s}$ , so  $v = 300\text{km/s}$ , using only two significant digits.

Successive images, such as in Figure 5 can allow more accurate estimations of kinematics.

### 4. DISCUSSION

To improve the smoothness and completeness of the perimeter detection, we have also tried a subsequent stage of the morphological geodesic active contour method from Márquez-Neila et al. (2014), based on level sets seeded with the interior of an initially-found contour. So far, it did not seem to succeed, mainly because of the of the various bright-dark alternating inner fronts, and also because of the background noise from the light of the stars. The latter could be further reduced by carefully realigning the images before subtraction, as suggested by Davies et al. (2009).

A possible line of improvement would be to better adapt the active contour methods to the already-found contour to fine-

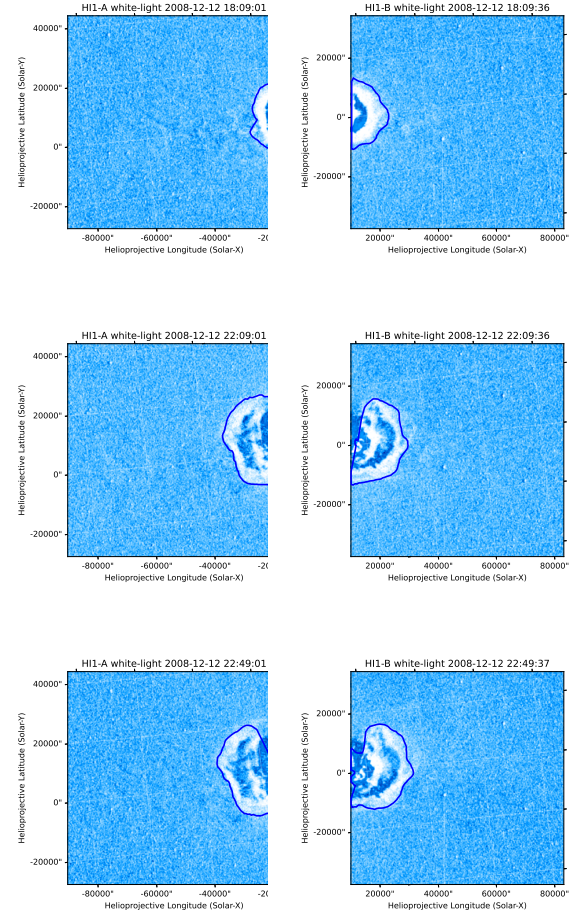


Figure 3. A few examples of processing

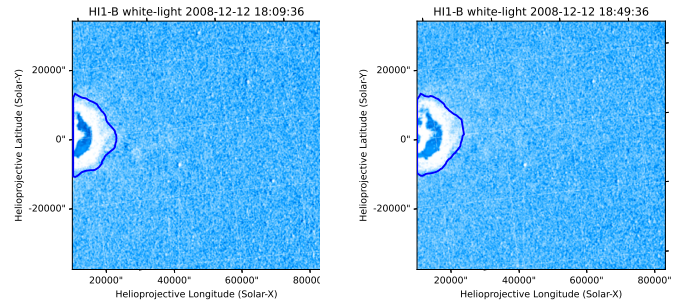


Figure 4. Two-image sequence to estimate front speed

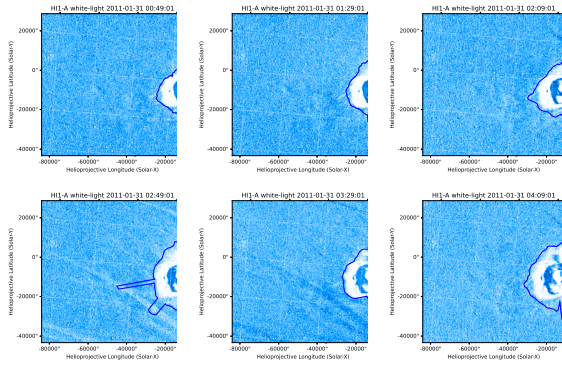
align it along less-contrasting borders. A more precise way to distinguish the far-away background could also help.

Finally, we are planning on working on integrating it with existing models to estimate CME velocities and 3-D shape changes, and then systematically comparing it with other methods.

### 5. ACKNOWLEDGEMENTS

We have implemented the algorithm in Python, and made it available at <https://github.com/MDNich/CME-Image-Edge-Detection-in-Python-from-STEREO-data>, and we are thus grateful to the community maintaining





**Figure 5.** Longer sequence

Numpy, SciPy and Matplotlib, as well as The SunPy Community et al. (2020).

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