Detection and Tracking of Coronal Mass Ejections

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Abstract. Coronal Mass Ejection (CME) events refer to the appearance of a new, discrete, white-light feature (with outward velocity) in a coronagraph. The huge amount of data provided by the pertinent instruments onboard the Solar and Heliospheric Observatory (SOHO) and, most recently, the Solar Terrestrial Relations Observatory (STEREO) makes the human-based detection of such events excessively time consuming. Although several algorithms have been proposed to address this issue, there is still lack of universal consensus about their reliability. This work presents a novel method for the detection and tracking of CMEs as recorded by the LASCO instruments onboard SOHO. The algorithm we developed is based on level sets and region competition methods, the CMEs texture being characterized by their co-ocurrence matrix. The texture information is introduced in the region competition motion equations, and in order to evolve the curve, a fast level set implementation is used.

Keywords: Level Sets, Region Competition, Textures, CMEs.

1 Introduction

The Solar and Heliospheric Observatory -SOHO- [1], an ESA/NASA mission, was launched in December 1995. The SOHO satellite consists of 12 instruments. Among them, we can mention the LASCO (Large Angle and Spectrometric Coronagraph) instrument, which consist of a suite of three coronagraphs: C1, C2, and C3. For technical details about the LASCO coronagraphs the reader is referred to [2].

A coronagraph is an instrument that blocks the light of the Sun's disk (creating an artificial eclipse of the Sun) to help reveal the faint signal in white light of the upper layers of the Sun's atmosphere, the so-called solar corona.

The events the solar physics community is interested in detecting and tracking are the so-called coronal mass ejections (CMEs). A CME is seen in the coronagraph field of view (FOV) as a new, discrete, white-light feature moving across its FOV with outward speed. Depending upon the direction of the magnetic field carried by the CME as it reaches Earth, surges in power grids leading to blackouts, and colorful auroras, can be produced.

The algorithms designed to address such an endeavor have to deal with a wide range of difficulties. To name a few, CMEs show up in different flavors, no one

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being like the other. And although the CMEs keep, in general, their morphological characteristics constant along their development in the images captured by the instruments, their intensity contrast with respect to the background can vary enormously from one image to the next. They can be followed by new ejections which are close in both space (as projected in the plane of the sky) and time (they can even be simultaneous), making their isolation even more difficult. Finally, the solar physics community still lacks of an objective definition (set of specific parameters) of what a CME is, e.g., how big and/or wide the intensity enhancement must be in order to consider the event a CME. Several attempts have already been made employing diverse techniques with different degrees of success. The reader is referred to [3] and references therein for a complete survey of existing techniques.

In this work we propose a novel approach for the detection and tracking of the CMEs. As in previous cases, the final objective is to generate a list of the events detected (and their properties) in a given time sequence of LASCO C2/C3 images. Our novel detection and tracking method of the CME events is based on the segmentation of their leading edge in individual frames. In particular, the resulting segmentation of a given frame in the sequence is taken as the initial estimation for the analysis of the following frame. In this way, the tracking problem is converted into a segmentation problem. The segmentation approach lies within the class of deformable template methods. They were introduced by Terzopoulos *et al.* in the late 80s and are based on the minimization of a functional. It is based on the region competition model [4].

In order to achieve better performance in the segmentation of the CMEs we propose a novel statistical model for the region competition model [4]. The proposed model, can deal with regions that are difficult to distinguish between each other using information from a single pixel, or where it is difficult to find a family of distributions to model regions.

This paper is structured as follows: in section 2 we introduce a novel segmentation method based on the region competition model; in section 3 we we explain the algorithms for detection and tracking of the CMEs; and in section 4 we present the results obtained by running the detection on image sequences captured by the C2 coronagraph. The conclusions, outlook, and future work are presented in section 5.

2 CME Segmentation Based on the Region Competition Model

2.1 Region Competition

As shown in [4], in region competition the goal is to segment an image into regions with homogeneous properties. A region is considered to be homogeneous if the values of the feature vector $v(x)$, defined for each pixel x in the image, follows a predetermined distribution $p(v(x)|\alpha)$, where α is the set of distribution parameters. Let us suppose that these vectors can be considered to be independent random variables, and that we have only two regions. Then, the level set motion equations are:

$$\frac{\partial \varphi}{\partial t} = \delta(\varphi) \left[\lambda \mathsf{div} \left(\frac{\nabla \varphi}{|\nabla \varphi|} \right) - \log \left(\frac{p(v(x)|\alpha_0)}{p(v(x)|\alpha_1)} \right) \right] \tag{1}$$

being φ the level set function, as described in [5].

A real time implementation proposed by Shi et al. [6] is based on the fact that the contours can be represented and evolved using only two double linked lists.

The region competition model [4] has inspired many different methods; to name a few, we can cite [7], that proposes a parametric model for supervised segmentation of textured images or [8] that proposes a non-parametric model.

In this work we present a novel method inspired in the region competition model to achieve a better performance in the segmentation of the CMEs. Our technique is based on the chisquare test, unlike the rest of the above mentioned techniques, which are based on either parametric or non-parametric statistics.

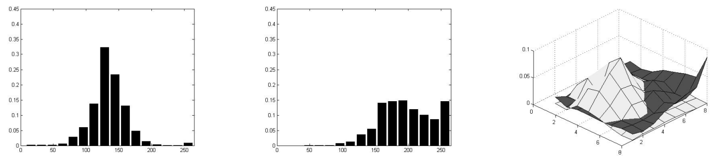
2.2 CME Segmentation

The objects we are interested to segment are the so-called coronal mass ejections. They are sometimes too faint to be observed clearly above the background level. One technique commonly used to contrast-enhance the CME events, with respect to the background, is to create running difference images. Each frame in the sequence is obtained as the difference between two successive images. Hence, features that do not change significantly in the time lapse between two successive images cancel out, leaving the intensity enhancements that characterize the CMEs practically alone. The typical signature of a CME event in this representation is that of a bright leading edge followed by a dark region and trailing material with a myriad of possible configurations.

Two big issues arise when we try to use the gray levels for each pixel x as the feature vector $v(x)$ within a region competition approach [4]. The first issue is related to the statistical model used for the CMEs, since their gray levels do not follow a normal distribution. Figs. 1 (a) and (b) show the histograms of the CME events and the background, respectively. The typical solution to this problem is to use non-parametric models like Parzen windows, Nearest-Neighbor-Estimation [9], and goodness-of-fit test (e.g., the chi-square test).

The second issue is the big overlapping between the histograms of both regions (the CME and the background) shown in the Figs. 1 (a) and (b). This fact makes the classification errors large. Hence, it is necessary to have information that captures the spatial complexity of the structure of the CMEs i.e., information that describes the textures of the CMEs.

The co-occurrence matrix $M_d^\phi(i,j)$, a second order histogram associated to an image I (with N_g gray levels), is defined as the frequency of pairs of pixels



(a) Histogram for the background from a running difference image.

(b) Histogram for a CME from a running difference image.

(c) Co-occurrence matrices for a CME (dark gray) and for the background (light gray). Each column corresponds to a bin of 32 gray levels.

Fig. 1. Histograms for a CME and the background shown in (a) and (b). Co–ocurrence matrix for a CME and the background shown in (c).

in which the first pixel has a gray value i and the second pixel has a gray value j, for a given displacement d and a given angle ϕ between both pixel positions.

Fig. 1 (c) shows the co-ocurrence matrices for the CME and the background. It is clear that the CME co-occurrence matrix does not follow a normal distribution. Therefore, the use of a goodness-of-fit test that can be incorporated in the level sets formalism is in order. The chi-square statistical test is a procedure that allows us to evaluate if the observed events follow a well-known distribution or if two sets of events have the same distribution up to certain level of significance [10]. The test for a second order histogram is defined as the result of evaluating Eq. (2).

$$\chi^2(R^1, R^2) = \sum_{ij} \frac{(R^1_{ij} - R^2_{ij})^2}{R^1_{ij} + R^2_{ij}}, \tag{2}$$

R^1 and R^2 being two second order histograms. The value of $\chi^2(R^1, R^2)$ is zero when the histograms are equal and grows when the histograms differ.

A natural way to include the chi-square test, is to modify the likelihood ratio in the region competition motion equations (1) in such a way as to include the non-parametric method, as shown in Eq. (3)

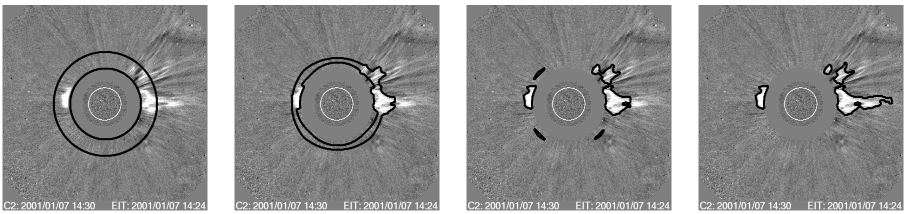
$$\frac{\partial \varphi}{\partial t} = \delta(\varphi)\left[\lambda \mathsf{div}\left(\frac{\nabla \varphi}{|\nabla \varphi|}\right) - \log\left(\frac{\chi^2(W(x,y), R^1)}{\chi^2(W(x,y), R^2)}\right)\right], \tag{3}$$

where $W(x, y)$ is the co-occurrence matrix of an $m \times m$ window centered at (x, y), and R^1, R^2 are the co-occurrence matrices that model the CMEs and background texture.

Eqs. (3) are the level sets motion equations, which can be solved using the method proposed in [6]. In this work, we use the fast solutions because of the large amount of information involved.

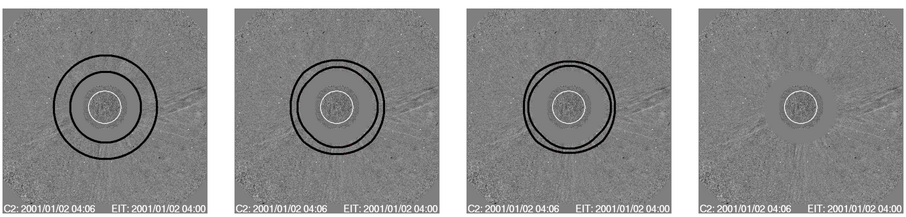
3 Detection and Tracking of CMEs

In order to detect the CME events, we propose to use Eqs. (3) to evolve a ring-like region around the occulting disk. For this, we use the estimated texture parameters of some previous instances of the event. In this way, if a CME is present, the region should evolve to detect it. Fig. 2 (a) shows the initial arrangement of the contour, and Figs. 2 (b) - (d) show the evolution of the contour to detect the CMEs for a given particular example. On the other hand, if a CME is not present, the region should collapse. Fig. 3 (a) shows the initial arrangement of the contour, and Figs. 3 (b) - (d) show the contour collapsing.



(a) Initial contour. (b) Evolved contour moving toward the CMEs. (c) Evolved contour moving toward the CMEs. (d) Final contour detecting the CMEs.

Fig. 2. Contour evolution when a CME is present



(a) Initial contour. (b) Evolved contour collapsing because no CME is present. (c) Evolved contour collapsing because no CME is present. (d) Collapsed contour.

Fig. 3. Contour evolution when no CME is present

In order to track the CMEs, we propose to use the resulting segmentation of the current image as initial contour for the next image, and evolve the contour according to the Eqs. (3). If the contour collapses, we suppose that the CME event has ended and we calculate the CME properties. Fig. 4 shows the result of the tracking a CME in a typical image sequence.

In what follows we show a couple of the CME properties that can be computed using the information obtained from the segmentation results.

For each point $\boldsymbol{p}$ in a coronographic image we can define a vector $\boldsymbol{v_p}$ with initial point in Sun's center $\boldsymbol{o}$ and terminal point in $\boldsymbol{p}$. The lateral edges of a

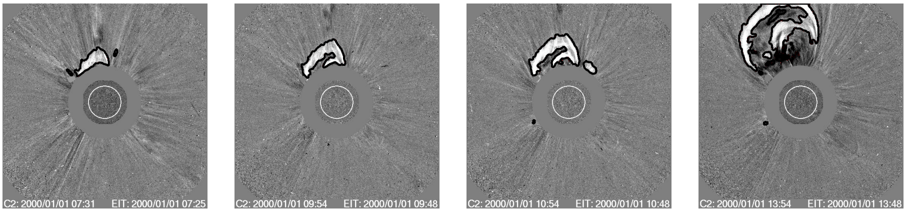


Fig. 4. Tracking of a CME

CME are the points $\boldsymbol{p}$ and $\boldsymbol{q}$ in the CME contour, such that the angle between the vectors $\boldsymbol{v_p}$ and $\boldsymbol{v_q}$ is maximum. The angular width of a CME is defined as the angle between the vectors $\boldsymbol{v_p}$ and $\boldsymbol{v_q}$. The central position angle of a CME is the angle of the vector $\boldsymbol{v_p} + \boldsymbol{v_q}$, measured counter-clockwise beginning at the North pole. Fig. 3 shows the properties of a segmented CME.

4 Results

In this section, we present the results obtained by running the detection and tracking algorithms based on texture, as exhibited in the previous section. We used a 7×7 window and a co-occurrence matrix of size 8×8.

The method developed was run on the C2 data set available at http://lasco-www.nrl.navy.mil/daily_mpg/2000_01/, which consists of more than 400 individual images. The full output of the algorithm (not shown here) can be compared to the list prepared by the LASCO team at http://cdaw.gsfc.nasa.gov/CME_list/. In particular, Table 1 shows a subset of the detected CMEs. Our list excluded those events with angular width less than 14 degrees or those that were detected in only one image. We found two CMEs in the LASCO catalog that our algorithm could not detect. They were rejected as events by our technique because of their sudden disappearance from the image sequence after they showed up. Likewise, there are three CMEs detected by our technique that do not appear

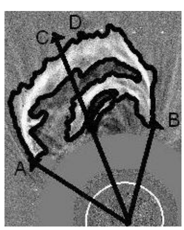


Fig. 5. Properties of a segmented CME. The vectors $\boldsymbol{A}$ and $\boldsymbol{B}$ are the lateral edges. The vector C is the result of the sum of the vectors $\boldsymbol{A}$ and $\boldsymbol{B}$. The point D is the farest point in the CME contour.

Table 1. Subset of the detected CMEs and their properties, compared to the LASCO catalog. Column CPA is Central Position Angle measured in degrees, column AWis AngularWidth measured in degrees, column LASCO indicates the presence of the event in the LASCO catalog.

LASCO Catalog			Our Algorithm		
Date and Time	CPA	AW	Date and Time	CPA	AW
2001/01/01 10:30:31	259	50	2001/01/01 09:30:00 AM	287	49
2001/01/02 05:54:05	222	49	2001/01/02 05:54:00 AM	220	25
2001/01/02 08:30:05	261	52	2001/01/02 09:30:00 AM	281	14
2001/01/02 12:30:05	226	128	2001/01/02 02:30:00 PM	210	41
2001/01/02 13:54:06	59	41	2001/01/02 01:54:00 PM	71	16
2001/01/02 17:54:28	152	60	DETECTED IN ONLY ONE IMAGE		
2001/01/02 21:30:10	71	114	2001/01/02 09:30:00 PM	55	52
2001/01/02 21:54:05	284	113	2001/01/02 10:06:00 PM	285	49
2001/01/03 04:30:05	192	53	2001/01/03 04:06:00 AM	200	28
2001/01/03 07:31:49	269	50	2001/01/03 07:31:00 AM	282	36
2001/01/03 10:54:06	270	40	NOT DETECTED		
2001/01/03 12:54:05	36	146	2001/01/03 12:30:00 PM	63	70
2001/01/03 14:30:05	273	35	2001/01/03 02:30:00 PM	275	20
2001/01/04 01:31:47	74	25	2001/01/04 01:31:00 AM	74	30
2001/01/04 07:54:08	112	46	2001/01/04 07:54:00 AM	122	21
2001/01/04 21:54:05	284	28	2001/01/04 09:54:00 PM	281	14
2001/01/04 23:06:05	69	38	2001/01/04 11:06:00 PM	75	25
2001/01/05 07:31:49	99	25	2001/01/05 07:31:00 AM	107	16
NOT PRESENT IN THE CATALOG			2001/01/05 11:06:00 AM	265	17
NOT PRESENT IN THE CATALOG			2001/01/05 11:30:00 AM	26	43
2001/01/05 11:54:05	111	44	2001/01/05 11:54:00 AM	126	21
2001/01/05 14:30:05	325	25	NOT DETECTED		
2001/01/05 17:06:05	Halo (BA)	360	2001/01/05 05:06:00 PM	HALO	
NOT PRESENT IN THE CATALOG			2001/01/05 02:06:00 AM	282	32

in the LASCO catalog. Visual inspection of the image sequence revealed that it was a detection of a narrow event, which maybe was discarded because of its narrow angular extent.

5 Conclusions

We have developed a new method for detecting and tracking CMEs in SOHO/ LASCO-C2 data. The novel method can detect and track CMEs having different shapes and intensities. The proposed method is a new approach in the field of CMEs tracking and detection, because it uses a statistical model to characterize the CMEs as seen in running difference images.

Our novel segmentation method is based on the region competition motion equations. It uses the chi-square test and the co-ocurrence matrix in order to correctly capture the texture of the CMEs as observed in running difference images. Future directions of this work include big challenges like, incorporating information of other instruments, dealing with missing chunks of images and improving the way the algorithms isolate the CMEs.

Acknowledgments

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