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Detection and tracking of coronal mass ejections based on supervised segmentation and level set

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A B S T R A C T

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 set and region competition methods, the CMEs texture being characterized by their co-occurrence 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.

1. Introduction

The Solar and Heliospheric Observatory (SOHO) (Domingo et al., 1995), 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 (Brueckner et al., 1995).

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 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 (Robbrecht and Berghmans, 2005) and references therein for a complete survey of existing techniques.

A novel method for the detection of the CMEs was proposed in (Goussies et al., 2008b), and in (Goussies et al., 2008a) it was extended to detection and tracking of the CMEs. In this work we further study the performance of this method on a new set of challenging images and compare its results with the results obtained using the method proposed in (Robbrecht and Berghmans, 2004). The goal is to generate a list of the detected CME events, together with their properties, from a given time sequence of LASCO C2/C3 images.

To this end, segmentation of the leading edge of CMEs is performed on individual frames, using the segmentation from the previous frame as an initial estimation. In this way, the tracking problem is converted into a segmentation problem. The segmentation approach is based on the region competition model (Zhu et al.,

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1995) and lies within the class of deformable models methods (Terzopoulos et al., 1988).

This paper is structured as follows: in Section 2 we introduce the segmentation method based on the region competition model; in Section 3 we explain the algorithms for detection and tracking of the CMEs; and in Section 4 we present the results obtained by running the detection method 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

In this work we propose to detect and track the CMEs using, the image segmentation by variational functional minimization approach. This technique can be traced back to (Kass et al., 1987). In practice, energy formulation based purely on image gradient are very sensible to initialization. Various extension to the snake model has been proposed to overcome some important limitations (Blake and Zisserman, 1987; Cohen, 1991; Berger, 1991; Fua and Leclerc, 1990).

A recent approach is the introduction of region-based terms to the functional (Mumford and Shah, 1989; Zhu et al., 1995; Paragios and Deriche, 1999, 2002; Rousson et al., 2003). Two different ways has been explored in the literature, supervised methods (Paragios and Deriche, 1999, 2002; Yezzi et al., 1999; Samson et al., 2000) and unsupervised methods (Zhu et al., 1995; Rousson et al., 2003; Chan and Vese, 2001). Supervised methods assume the region models to be known or learned in a previous stage, while unsupervised methods need to jointly perform the segmentation and estimate the region models, which are normally solved by minimizing the functional with respect to the region boundary and region models alternatively.

We present a novel supervised segmentation method inspired in the region competition model to achieve a better performance in the segmentation of the CMEs. Our technique is based on the chi-square test, unlike (Kim et al., 2005; Paragios and Deriche, 2002) which are based on either parametric or non-parametric statistics.

This section is structured as follows, first we revisit the region competition model. Second we formulate the CME segmentation problem using the region competition model and explain the issues found. Third we propose our novel supervised segmentation technique for CMEs.

2.1. Region competition

As shown in (Zhu et al., 1995), in region competition the goal is to segment an image into a family of regions $\mathscr{R} = \{\boldsymbol{R}_i\}_{i=1,\dots,N}$ such that the points in each region share some image characteristics. In (Zhu et al., 1995) it has been proposed that the intensity values of the points inside each region are consistent with having been generated by one of a family of pre-specified probability distributions $P(v(\vec{x}) : \vec{\alpha}_i)$, where $\vec{\alpha}_i$ are the parameters of the distribution for the region $\boldsymbol{R}_i$ and $v(\vec{x})$ are the values of a feature vector defined for each pixel $\vec{x}$. Let us suppose that these vectors can be considered to be independent random variables, and that we have only two regions. Then, the proposed functional is:

$$E^{ZY}(\boldsymbol{R}_1, \boldsymbol{R}_2, \vec{\alpha}_1, \vec{\alpha}_2) = -\int_{\boldsymbol{R}_1} \log P(v(\vec{x}) : \vec{\alpha}_1) d\vec{x} - \int_{\boldsymbol{R}_2} \log P(v(\vec{x}) : \vec{\alpha}_2) d\vec{x} + \lambda \oint_{\partial \boldsymbol{R}_1} ds \tag{1}$$

being $\partial\boldsymbol{R}_1$ the boundary of the region $\boldsymbol{R}_1$. The regions that minimizes the functional are the desired family of regions $\mathscr{R}$. The first and second term is the sum of the cost for coding the intensity of every $\vec{x}$ pixel inside the $\boldsymbol{R}_i$ according to its distribution. The third term, is a regularization term and penalizes large boundaries. The parameter $\lambda > 0$ is a weighting constant controlling the regularization. A different explanation for a similar energy functional can be found in the interesting work (Rousson, 2004).

2.1.1. Level set based minimization

Although the suggested functional in Eq. (1) describes the problem quite accurately, their minimization is very difficult. Level set based methods (Osher and Sethian, 1988) are a way to solve this problem. The methods has a lot of attractive properties. First, level set can describe topological changes in the segmentation. Second, it is not necessary to discretisize the contours of the objects. Also, geometric properties of the boundaries of the regions can be easily approximated from the level set representation.

The functional in Eq. (1) can be expressed in the level set formalism (Sethian, 2007):

$$E^{ZY}(\Phi, \vec{\alpha}_1, \vec{\alpha}_2) = -\int_{\Omega} H(\Phi(\vec{x}))P(v(\vec{x}) : \vec{\alpha}_1) + \int_{\Omega} (1 - H(\Phi(\vec{x})))P(v(\vec{x}) : \vec{\alpha}_2) d\vec{x} + \lambda \int_{\Omega} |\nabla H(\Phi(\vec{x}))| d\vec{x}, \tag{2}$$

where $\Omega \subseteq \Re^2$ is the image domain, $\Phi : \Re^2 \to \Re$ is the level set function representing the regions $\boldsymbol{R}_1$ for $\Phi > 0$ and $\boldsymbol{R}_2$ for $\Phi < 0$, as well as the contour $\partial\boldsymbol{R}_1$ for $\Phi = 0$. The Heaviside function $H(\Phi) = 0$ for $\Phi < 0$ and $H(\Phi) = 1$ for $\Phi > 0$.

A necessary condition for the function $\Phi^{\min}$ to be a local minima of E^{ZY}, given $\vec{\alpha}_1$ and $\vec{\alpha}_2$, is to satisfy the Euler–Lagrange equation

$$\frac{\partial E^{ZY}}{\partial \Phi}(\Phi^{\min}, \vec{\alpha}_1, \vec{\alpha}_2) = 0. \tag{3}$$

A numerical approximation to the function $\Phi^{\min}$ can be calculated using the gradient descent method. Embedding the function $\Phi : \Re^2 \to \Re$ into a family of one-parameter functions $\Phi : \Re^2 \times \Re^+ \to \Re$. Starting at a initial function Φ^0 and moving opposite to the Euler–Lagrange equation we find the local minima solving the partial differential equation:

$$\begin{cases} \Phi(\vec{x}, 0) = \Phi^0(\vec{x}), \\ \frac{\partial \Phi}{\partial t}(\vec{x}, t) = \|\nabla \Phi(\vec{x}, t)\| \left[\lambda \operatorname{div}\left(\frac{\nabla \Phi(\vec{x}, t)}{\|\nabla \Phi(\vec{x}, t)\|}\right) - \log\left(\frac{P(v(\vec{x}) : \alpha_1)}{P(v(\vec{x}) : \alpha_2)}\right)\right]. \end{cases} \tag{4}$$

The function $\Phi^{\min}$ is numerically approximated by $\Phi(\vec{x}, t)$ when $t \to \infty$.

A real time implementation proposed by Shi and Karl (2005) is based on the fact that the boundaries $\partial \mathrm{R}_i$ can be represented and evolved using only two double linked lists.

2.2. CME segmentation based on the supervised region competition model

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 (Zhu et al., 1995). The first issue is related to the statistical