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Postprint: Coronal Mass Ejection Detection Method Based on Faster R-CNN

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Abstract

Coronal Mass Ejection (CME) is a violent solar eruption phenomenon that exerts tremendous impacts on space weather and human life. Therefore, CME detection is of great significance for forecasting CMEs and ensuring the safety of human production and daily life. Existing detection methods predominantly employ approaches based on manually defined features and manually determined thresholds. However, since manually defined features cannot adequately characterize CMEs and universally applicable thresholds are difficult to establish, the detection efficacy of current CME detection methods remains to be improved. This paper proposes a coronal mass ejection detection algorithm based on Faster R-CNN. The method first integrates information from three renowned CME catalogs—CDAW, SEEDS, and CACTus—to manually annotate a dataset comprising 9113 coronal images. Subsequently, according to the characteristics that CMEs possess fewer image features compared to natural images and exhibit differences in target scales, improvements are made to Faster R-CNN in feature extraction and anchor selection. Utilizing the CME annotation data from June 2007 as the test set, the proposed algorithm successfully detected all 22 strong CME events and 138 out of 151 weak CME events, with detection errors for characteristic parameters such as central angle and angular width of CME events being within 5 degrees and 10 degrees, respectively.

Full Text

Detection of Coronal Mass Ejections Based on Faster R-CNN

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Abstract

Coronal Mass Ejection (CME) is a powerful solar eruption phenomenon that significantly impacts space weather and human life. Therefore, CME detection is crucial for forecasting CMEs and ensuring the safety of human activities. Existing detection methods predominantly rely on manually defined features and thresholds. However, manually defined features cannot adequately characterize CMEs, and selecting universally applicable thresholds is challenging, limiting the effectiveness of current CME detection approaches. This paper proposes a CME detection algorithm based on Faster R-CNN. We first created a manually annotated dataset comprising 9,113 coronal images by integrating information from three prominent CME catalogs: CDAW, SEEDS, and CACTus. Considering that CME images contain fewer features than natural images and that target dimensions differ from those in natural images, we improved the Faster R-CNN architecture in terms of feature extraction and anchor selection. Using CME annotation data from June 2007 as our test set, the algorithm successfully detected all 22 strong CME events and 138 out of 151 weak CME events, with detection errors for characteristic parameters such as central angle and angular width within 5 and 10 degrees, respectively.

Keywords: Coronal Mass Ejection; object detection; image processing

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CME is an intense space weather phenomenon where coronal material is ejected from the Sun' s corona into interplanetary space [?]. Due to their enormous velocity and energy, and differences in magnetic field, speed, and temperature from the background solar wind, CMEs cause solar wind disturbances during propagation through interplanetary space, sometimes triggering extreme space weather events such as magnetic storms. These events can lead to satellite malfunctions and data loss in space, power system failures on the ground, and shortwave communication disruptions. To mitigate these impacts, CME forecasting is essential, and CME detection forms the critical foundation for such forecasting.

Satellites such as SOHO (Solar and Heliospheric Observatory) and STEREO (Solar Terrestrial Relations Observatory) have provided extensive coronal image data. [Figure 1: see original paper] shows a LASCO C2 image and its running difference image from SOHO. CME targets appear in coronal images as bright, complex-textured enhanced structures trailing a dimmer dark region. Based on these images, researchers have proposed various detection methods to identify CME occurrence frequency, angle, velocity, mass, energy, and other characteristics. Existing CME detection methods can be categorized into traditional detection methods and learning-based detection methods. Detailed reviews of CME detection methods are available in reference [?].

Traditional detection methods utilize grayscale or texture features of coronal images combined with spatial domain image processing techniques. Berghmans et al. [?][?] developed the Computer Aided CME Tracking software package (CACTus), which employs Hough transforms and morphological operations to detect CMEs and extract information about their position, angle, and velocity. The CACTus catalog generated by this system was the first automatically detected CME catalog. Olmedo et al. [?][?] proposed the Solar Eruptive Event Detection System (SEEDS), which uses grayscale information from coronal images to detect CME leading and trailing edges. The SEEDS catalog, together with the CACTus catalog and the Coordinated Data Analysis Workshop Data Center (CDAW) catalog, constitute the three major reference CME catalogs, with CDAW being manually annotated.

Manual CME detection is time-consuming and labor-intensive, and weak CME detection results are often subject to human subjective factors. Consequently, computer-based CME detection has become an inevitable trend. However, traditional automatic CME detection methods primarily rely on threshold-based discrimination, which has several limitations: (1) thresholds are difficult to determine, and (2) selected thresholds struggle to accommodate both strong and weak CMEs simultaneously. When detection performance for strong CMEs is good, the detection of weak CMEs with less distinct features deteriorates, and errors in detecting parameters such as angular width and central angle become significant.

Learning-based detection methods first train CME classifiers using machine learning approaches and then use these classifiers to distinguish CMEs from background information. Zhang et al. [?][?] proposed an AdaBoost-based coronal image recognition method that directly identifies CMEs in sector-shaped regions. In contrast, Yin et al. [?] proposed a learning-based method for CME detection in polar coordinates, extracting texture, grayscale, and HOG (Histogram of Oriented Gradient) features to train a multi-feature fusion classifier for CME detection. However, learning-based methods primarily rely on manually defined features for CME modeling. Since CME image features are complex and highly variable, with significant differences between different CMEs, manually defined features provide poor modeling effectiveness.

Faster R-CNN [?] is currently one of the best object detection algorithms. Based on deep learning neural networks, Faster R-CNN autonomously learns dataset features to train an excellent object detection network. The algorithm achieved a mAP (mean Average Precision) of 73.2% on the PASCAL VOC dataset [?], demonstrating strong detection performance and has been applied to various detection scenarios [?][?]. The feature extraction network of Faster R-CNN can model CMEs effectively, addressing the problem that manually defined features cannot adequately represent CMEs. Additionally, the classifier trained by the neural network in Faster R-CNN performs better than those in learning-based methods. For these reasons, this paper proposes a CME detection method based on Faster R-CNN. Our main contributions include: (1) annotating a target detection dataset containing 9,113 coronal images by referencing CME catalogs including CDAW, CACTus, and SEEDS and performing manual verification; (2)

improving the Faster R-CNN model to better suit the characteristics of coronal images.

1 Deep Learning Algorithms and Faster R-CNN

With the development of machine learning and improvements in computer hardware, deep learning-based object detection algorithms have emerged continuously. Among these algorithms, the R-CNN (Region-based Convolutional Neural Networks) series (with Faster R-CNN as a prominent representative), SSD (Single Shot MultiBox Detector) [?], and YOLO (You Only Look Once) [?] are several algorithms with outstanding performance. These algorithms can be divided into two main categories based on processing flow: one-stage detection algorithms and two-stage detection algorithms. Two-stage detection algorithms process object detection in two steps: first, selecting a certain number of candidate boxes through selective search algorithms or region proposal networks, then determining the category and location of target objects through classification and regression networks. Due to the time-consuming candidate box selection stage, two-stage detection algorithms have slightly poorer real-time performance but higher accuracy. To improve real-time performance, Wei Liu et al. and Joseph Redmon et al. proposed one-stage detection algorithms such as SSD and YOLO, which eliminate the need for candidate box selection and directly generate target categories and locations from the original image, offering good real-time performance but slightly lower accuracy than two-stage algorithms. Both categories of algorithms far exceed traditional detection methods in performance on natural image datasets. Through experimental comparison, Faster R-CNN demonstrates better detection robustness than SSD and YOLO for non-natural images such as coronal images, leading us to select Faster R-CNN as the base network for building our CME detection network.

Faster R-CNN is an improved version of Fast R-CNN [?]. Fast R-CNN uses selective search algorithms for candidate box selection, which is time-consuming and becomes a bottleneck for improving real-time performance. Faster R-CNN replaces the selective search algorithm with a Region Proposal Network (RPN), improving candidate box selection efficiency without affecting detection accuracy. The network model is shown in [Figure 2: see original paper] and can be divided into three modules: feature extraction network, region proposal network, and classifier.

The feature extraction network uses convolutional layers, activation layers, and pooling layers to extract feature maps from images. Faster R-CNN employs the VGG16 network [?] as its feature extraction network. The feature maps are shared for subsequent region proposal network and classifier processing.

The region proposal network processes the feature maps output by the feature extraction network using two branches. One branch selects candidate boxes that may contain targets based on anchor points, while the other branch generates the probability of candidate boxes containing targets. Combining these two branches yields the position and confidence of candidate targets. Anchor points are the essence of RPN, representing a set of rectangular boxes generated based on each feature point in the feature map. The RPN sets nine anchors composed of three scales and three aspect ratios. The three scales are 64, 128, and 256, and the three aspect ratios are 1:1, 1:2, and 2:1. Each element in the feature map generates nine candidate boxes based on these nine anchors. During training, 128 positive candidate boxes and 128 negative candidate boxes are randomly selected from each image.

The classifier utilizes feature maps and region proposals to calculate the category of each candidate box through fully connected layers and softmax function, outputting a category probability vector. Simultaneously, it uses bounding box regression to calculate position offsets for each candidate box, obtaining more accurate target locations.

2 Improved Faster R-CNN Framework

While Faster R-CNN performs well on natural image data, its direct application to coronal image detection yields poor results due to differences between coronal and natural images, primarily for two reasons: (a) The difference images used in our dataset are grayscale images containing fewer color and texture features than natural images in datasets such as PASCAL VOC and COCO [**?**]. (b) The size of CME targets in coronal images differs from target sizes in natural image datasets, making the original anchors designed for natural images less effective.

Based on these considerations, we improved Faster R-CNN in terms of feature extraction network and anchor parameters according to the characteristics of coronal images. The improved Faster R-CNN model is shown in [Figure 3: see original paper].

2.1 Feature Extraction Network Improvement

In object detection, the VGG16 network can extract abstract semantic features of targets. However, when applied to non-natural images such as coronal images, it suffers from feature degradation and loss of shallow features as convolutional depth increases. The ResNet101 [**?**] network addresses this degradation problem through residual connections, which allow information from previous residual blocks to flow unimpeded into subsequent blocks, improving information flow and preserving shallow features while avoiding gradient vanishing and degradation problems caused by overly deep networks. Coronal images contain less information than natural images and are prone to degradation as convolutional depth increases, necessitating the preservation of shallow features. Therefore, our algorithm selects ResNet101 as the feature extraction network.

Coronal images exhibit clear temporal continuity, with adjacent temporal images showing similarity. [Figure 4: see original paper] shows running difference images at 15:12 and 15:24 on January 1, 2014. As coronal material ejects outward over time, the material in the later image is slightly farther from the solar center than in the previous image, while the background similarity between the two images remains high. As shown in Figure 4: see original paper(d), after converting coronal image difference maps to polar coordinates, CME targets in adjacent coronal images basically overlap in the horizontal direction, with the CME target height in the later image slightly increased in the vertical direction. Due to the similarity in features and positions of CME targets in adjacent temporal images, fusing features from adjacent images can enhance target feature representation and better distinguish CME targets from background. To better utilize the temporal sequence similarity of coronal images and strengthen CME target feature modeling, we fuse features from the current moment with those from the previous two moments when detecting a coronal image at a certain time. Specifically, coronal images from three moments pass through the same feature extraction network to generate three feature maps, which are then fused into a new feature map through fully connected layer convolution. This new feature map serves as input for the RPN and classifier.

2.2 Modified Anchors

K-means [?] is a distance-based clustering algorithm that uses distance as a similarity metric, assuming that closer objects have greater similarity. The algorithm aims to obtain compact and independent clusters by grouping objects with small distances.

The original anchors in Faster R-CNN are designed for natural images and generate relatively large rectangular boxes. However, CME targets have smaller areas and more varied aspect ratios that do not match the original anchors. Based on our dataset, we clustered the areas and aspect ratios of CME targets to obtain appropriate combinations. According to the clustering results from k-means, we designed nine anchors as combinations of scales (16, 32, 64) and aspect ratios (1:1, 1:2, 1:4).

3 Dataset Annotation

Currently, no CME dataset exists for deep learning and object detection research. We created our own dataset by downloading LASCO C2 coronal image data from SOHO for eight months: June-September 2007 and January-April 2014. LASCO C2 images were processed through morphological operations, inter-frame differencing, and polar coordinate transformation to obtain polar difference images. Difference images better reveal CME target motion trends and reduce the influence of background information, noise, and non-CME features such as streamers. Polar coordinate images are more conducive to rectangular box annotation and detection than original coronal images. Therefore, we used polar difference images of coronal images as input to our detection model.

CME classification: (a) strong CME; (b) weak CME.

Our dataset annotated CMEs by referencing information from the three major catalogs—SEEDS, CDAW, and CACTus—with manual verification and fine-tuning. Following CDAW's CME classification definitions, we categorized CMEs into strong and weak CMEs. Strong CMEs [?] refer to large amounts of material ejected from the corona during intense solar activity, appearing in coronal images as large bright feature areas with expansion patterns, fast expansion speeds, obvious brightness features, and ejection angular widths generally greater than 40 degrees—similar to CMEs with empty type markers in the CDAW catalog. Weak CMEs [?] refer to coronal material ejected during pre- and post-solar activity periods, appearing in coronal images as less ejected material, less prominent bright features, angular widths generally less than 30 degrees, and typically presenting as small dark regions or faint thin strips—similar to CMEs marked as weak or very weak in the CDAW catalog. As shown in [Figure 5: see original paper], subfigures (a) and (b) show rectangular box regions representing strong and weak CMEs, respectively, with right subfigures showing enlarged views of these regions.

shows CME markings from the three major catalogs during June 1-3, 2007, with 16 CME events marked in total, of which 4 were marked by all three catalogs. While all three catalogs adequately marked CME events, significant differences and individual deficiencies exist among them. For example, CME event 1 in was marked by CDAW at 00:06 on June 1, 2007, but not by CACTus or SEEDS. Conversely, there were cases where CACTus or SEEDS marked a CME event that the other two catalogs missed. As shown in CME event 3, all three catalogs marked the CME event starting at 07:30 on June 1, 2007, but with substantially different position information. Sometimes, one catalog would mark two adjacent CME events in angle, while another would mark them as a single event. Additionally, some CME positions marked by the catalogs differed from the true positions in the images.

To address these issues, we first automatically generated target boxes using information from the three catalogs, then manually adjusted them using the lambelImg tool. The automatic generation and manual adjustment process involved: (1) taking the union of CME event information marked by the three catalogs; (2) removing duplicates—when a CME event was marked by two or more catalogs, we prioritized CDAW information, followed by SEEDS if CDAW had no marking, and annotated the coronal image accordingly; (3) manual verification—when catalogs produced false detections, we manually removed them, and when reference catalog positions deviated significantly from true CME positions, we performed manual adjustments. During manual adjustment, CME target edges were defined as pixels where the target region block' s grayscale value exceeded the image average grayscale by 5. When the edge distance between two target blocks was less than 10 pixels, the two blocks were merged into a single CME target, with edges redefined as the merged target' s boundaries, and rectangular target boxes were annotated along these edges.

As shown in Figure 6: see original paper, three images represent CDAW, SEEDS, and our dataset' s annotation results for a coronal image at 12:54 on May 1, 2007, with our dataset's annotation primarily referencing and fine-tuning CDAW catalog information. Figure 6: see original paper shows SEEDS, CACTus, and our dataset' s annotation results for a coronal image at 18:12 on February 16, 2014 (CDAW marked no CME on this image), with our annotation primarily referencing and fine-tuning SEEDS catalog information. Figure 6: see original paper shows false detection cases from the three catalogs: the first image shows a CME region annotated by CDAW at 11:06 on May 2, 2007, where no CME target existed; the second shows a CME region detected by SEEDS at 03:24 on February 19, 2014, which was actually the trailing edge of an already ejected CME, not a new event; the third shows a CME region detected by CACTus at 04:24 on February 19, 2014, where no CME target existed. These false detections were removed during manual verification.

Based on these criteria, we annotated eight months of coronal image data downloaded from SOHO, comprising 19,524 images total, with 9,113 images containing CME targets, annotating 1,537 CME events and 13,599 bounding boxes. We selected data from July-September 2007 and January-March 2014 as the training set, April 2014 as the validation set, and June 2007 as the test set. The training set contains 6,255 images with 128 strong and 997 weak CME events; the validation set contains 1,983 images with 44 strong and 195 weak CME events; and the test set contains 875 images with 22 strong and 151 weak CME events.

4 Experimental Training and Results Verification

Our model was trained on a Lenovo computer with a 2.6GHz CPU, 16.00GB RAM, and a GTX1070 GPU. We fine-tuned our network using our custom dataset based on ImageNet pretrained parameters. The initial learning rate was set to 0.001, reduced to 0.0001 at 35,000 iterations, with a maximum of 70,000 iterations. To evaluate detection performance, we used recall, precision, and mAP metrics, all averaged across both strong and weak CME categories.

4.1 Validation of Faster R-CNN Improvements

To validate the effectiveness of our improvements to Faster R-CNN, we designed five comparative experiments: original Faster R-CNN, Faster R-CNN+ResNet101, Faster R-CNN+three-temporal feature fusion, Faster R-CNN+anchor improvement, and our full model incorporating all improvements. Experimental results on our dataset' s validation set are shown in .

Analyzing the impact on recall, each improvement provided enhancement, with anchor improvement showing the best effect and ResNet101 showing smaller improvements. This is because improved anchors better match CME target areas and aspect ratios. For precision, improved anchors also achieved the best enhancement, with the other two improvements showing notable gains. Finally, since ResNet101 preserves shallow features of coronal images and three-temporal feature fusion strengthens current CME features by leveraging temporal correlations, all three improvements increased mAP by over 10%, demonstrating significant enhancement.

Our full model with all three improvements outperformed Faster R-CNN across all metrics, with recall increasing by 22.2%, precision by 19.7%, and mAP by 22.4%. This confirms that our improvements to Faster R-CNN based on coronal image characteristics are effective.

4.2 Comparison with Different Object Detection Algorithms

To verify our model' s CME detection effectiveness, we tested four detection models—our model, Faster R-CNN, SSD, and YOLO V3 [?]—on our dataset' s validation set. Results are shown in .

One-stage detection algorithms like SSD and YOLO V3 perform poorly on CME detection due to extracting only deep features and lacking second-stage bounding box regression. Faster R-CNN also has these limitations but achieves better robustness and detection effectiveness through its two-stage regression. While Faster R-CNN performs slightly better than SSD and YOLO V3, our algorithm demonstrates the best detection performance with an mAP of 81.5%.

4.3 Comparison with Traditional CME Catalogs

As shown in [Figure 7: see original paper], a CME event appears in polar coordinate images as a series of bright CME targets that overlap horizontally and gradually rise vertically. In other words, when a CME target in the current temporal image overlaps horizontally with a CME target in the previous image and rises vertically, they belong to the same CME event. Using this characteristic, we defined CME event authentication criteria on our model' s detection results: two target boxes in adjacent temporal images belong to the same CME event if their horizontal overlap rate exceeds 50% and they rise vertically over time, where overlap rate is defined as the overlapping width in the horizontal direction divided by the width of the smaller box. Based on these criteria, we identified multiple CME target boxes for each CME event. If more than two-thirds of these boxes are weak CME targets, the event is classified as weak; otherwise, it is strong. Angular width is defined as the difference between the maximum right boundary and minimum left boundary of the event' s target boxes, while central angle is the minimum left boundary plus half the angular width. Using these definitions, we generated our CME catalog by traversing our model' s detection results. Our June 2007 CME catalog is published at https://gitee.com/xian-xianggui/faster-rcnn-cme.

[Figure 7: see original paper] shows detection results for the first three frames of a weak CME event starting at 16:54 on June 9, 2007, with red boxes for CDAW results, yellow for SEEDS, white for our dataset annotations, and no detection by CACTus. Subfigures (a)-(c) show polar coordinate running difference images at 16:54, 17:06, and 17:30, while (e)-(f) show corresponding coronal image difference maps.

Currently, there is no clear academic definition of CME events, nor public evaluation standards for CME detection accuracy. Our annotated dataset references the three major CME catalogs (CDAW, CACTus, SEEDS), integrates their advantages, and undergoes manual verification and adjustment, providing certain accuracy and comprehensiveness. Using our custom dataset as a reference standard, we compared our catalog' s detection performance with existing catalogs, evaluating CME detection effectiveness on June 2007 data from two perspectives: CME event quantity detection and CME feature parameter detection.

4.3.1 Correct CME Detection Quantity For CME event quantity detection, correctly identifying strong CMEs is crucial due to their significant impact on space weather and human life. We first compared strong CME detection quantities with existing catalogs. Additionally, since current detection methods generally perform worse on weak CMEs, improving weak CME detection accuracy represents an important objective.

Due to CME definition variations and background streamer effects, manually annotated catalogs like CDAW and automatic detection catalogs exhibit differences in feature parameters for the same CME event. Although parameters for the same event vary across catalogs, they can be identified as the same event based on correlation. We define a correctly detected CME event as one where the horizontally overlapping angle between the catalog-marked event and dataset-annotated event exceeds 50%, and the starting time difference is within 1.5 hours. [Figure 7: see original paper] shows a correctly detected CME: CDAW' s detected position has 100% overlap with our dataset and identical start time (16:54), making it correct; SEEDS also shows 100% overlap with only a 12-minute time difference, also correct.

[Figure 8: see original paper] compares correct CME quantities across catalogs. Our June 2007 test set annotated 22 strong and 151 weak CMEs. For strong CMEs, CDAW, SEEDS, and CACTus detected 22, 11, and 9 events, respectively. For weak CMEs, they detected 127, 15, and 11 events, respectively. Our algorithm detected all 22 strong CMEs and 138 weak CMEs, achieving the best performance for both categories. This is because our dataset annotation integrated information from all three catalogs, including CMEs present in SEEDS or CACTus but absent in CDAW. [Figure 9: see original paper] shows detection results for strong and weak CMEs.

4.3.2 CME Feature Parameters The accuracy of CME feature parameter detection is an important evaluation metric. Using our June 2007 test set as a benchmark, we compared our algorithm' s performance against the three major catalogs in detecting central angle and angular width.

Since CME events appear in polar coordinate images as horizontally overlapping, vertically rising bright targets, we defined the minimum left edge of multiple target boxes as the event' s left edge and the maximum right edge as its right edge, with the width between them being angular width and the center point angle being central angle. Our algorithm and the three catalogs simultaneously marked 9 strong and 10 weak CME events. Using these 19 events as subjects and our test set parameters as the standard, we calculated each catalog' s average errors in central angle and angular width relative to the test set, shown in [Figure 10: see original paper].

[Figure 10: see original paper] shows that our algorithm and CDAW catalog have small differences from the test set in central angle and angular width. Our catalog' s average errors are 3.3 degrees for central angle and 8.2 degrees for angular width, while CDAW' s average errors are 5.6 and 10.4 degrees, respectively. SEEDS and CACTus catalogs, which use simple threshold methods, exhibit relatively larger average errors. Our algorithm achieves more accurate detection of CME central angles and angular widths than existing catalogs.

5 Conclusion

Existing CME detection methods struggle with adequate CME modeling and selecting universal thresholds due to reliance on manually defined features and segmentation thresholds, resulting in suboptimal detection performance. This paper introduces a deep learning-based object detection model for CME detection. By referencing CDAW, CACTus, and SEEDS catalogs to annotate a CME dataset and training a feature extraction network on this custom dataset, our method effectively extracts CME feature information. Additionally, the deep learning detection model autonomously trains its classifier, avoiding the drawbacks of manual threshold setting and achieving better CME detection results.

Using our June 2007 test set as a benchmark, our algorithm demonstrates three advantages: (1) Detection accuracy reaches 100% for strong CMEs and 91.4% for weak CMEs, with an overall accuracy of 92.5%–6.4%, 72%, and 81% higher than CDAW, SEEDS, and CACTus, respectively. (2) It can detect weak CME events missed by CDAW, some of which were annotated as weak CMEs by SEEDS or CACTus, while others can be certified as weak CMEs based on our definition. (3) On our annotated test set, our algorithm detects CME central angles and angular widths more accurately than existing catalogs.

This work has two innovative contributions. First, we introduced deep learning methods for autonomous CME feature extraction, achieving better CME representation and detection performance. Second, by referencing the three major CME catalogs and performing manual verification, we annotated a CME dataset for object detection that integrates the strengths of all three catalogs and can serve as a reference for future CME detection research. Although this study has made progress in CME detection, future improvements could include: (1) Incorporating additional information such as velocity and acceleration parameters from the three major catalogs, as our current dataset information is relatively limited. (2) Measuring additional CME features such as velocity, which our current algorithm does not detect.

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