Postprint: Identification and Tracking of Coronal Loop Oscillations Based on Phase Consistency and Directional Filtering

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Abstract

Accurate identification and tracking of coronal loop structures facilitates better research and analysis of coronal loop characteristics and their relationship with flare eruptions and coronal mass ejections. A method for identifying and tracking coronal loop oscillations based on phase congruency and directional filtering is proposed. The identification process is as follows: First, phase congruency technique is used to identify coronal loop features in solar images; second, the identified images are binarized; next, directional filtering is employed to remove non-coronal-loop structural features; then, morphological processing is performed; finally, quadratic curve fitting is applied to the identification results. The proposed algorithm was applied to identify and track coronal loop oscillations observed on September 6, 2011 by the Solar Dynamics Observatory (SDO) in the Fe IX 17.1 nm band, and the results verified the feasibility and accuracy of the proposed algorithm. It is demonstrated that the proposed algorithm can be utilized for research and analysis of coronal loop characteristics and oscillation processes.

Full Text

Identification and Tracking of Coronal Loop Oscillations Using Phase Congruency and Directional Filtering

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Abstract: Accurate identification and tracking of coronal loop structures facilitates better research and analysis of loop characteristics and their relationship with flare eruptions and coronal mass ejections. This paper proposes a method for identifying and tracking coronal loop oscillations based on phase congruency and directional filtering. The identification process proceeds as follows: First, phase congruency techniques are employed to identify coronal loop features in solar images. Second, the identified images undergo binarization. Directional filtering is then applied to remove non-loop structural features, followed by morphological processing. Finally, the identification results are fitted with quadratic curves. The proposed algorithm was used to identify and track coronal loop oscillations observed by the Solar Dynamics Observatory' s Atmospheric Imaging Assembly in the Fe IX 17.1 nm band, with results validating the feasibility and accuracy of the method. This demonstrates that the algorithm can be applied to study and analyze coronal loop characteristics and oscillation processes.

Keywords: Phase congruency; Directional filtering; Coronal loop oscillation; Oscillation period

1. Introduction

The corona, located in the outermost layer of the solar atmosphere, exhibits bright ring-like structures known as coronal loops. These loops represent manifestations of solar magnetic field structure and are closely related to coronal mass ejections and solar storms. Studying coronal loops and their evolution is crucial for understanding magnetic activity in the solar atmosphere and forecasting space weather. Coronal loops form when hot plasma, confined by coronal magnetic fields, emits radiation to create bright, arching structures.

Solar flare eruptions and coronal mass ejections release substantial energy, causing dramatic changes in local magnetic field structures that induce oscillations in nearby coronal loops. These oscillations occur not only in individual loops but also across multiple loop structures simultaneously. Research indicates that such oscillations represent a form of standing wave, though each loop often displays distinct oscillation characteristics due to differences in frequency, phase, and decay coefficient. Investigating these features provides valuable insights into how flares and coronal mass ejections influence the coronal magnetic field.

However, accurately identifying and extracting coronal loop structures presents significant challenges. First, the plasma confined by coronal magnetic fields is non-uniformly distributed, resulting in blurred loop boundaries that complicate extraction. Second, although loop structures exhibit relatively high intensity, intensity variations are subtle, and individual loops are closely spaced and intertwined, causing overlapping ring structures in two-dimensional images. Third, the complexity of magnetic activity leads to diverse loop morphologies, including broken ring structures. Fourth, non-loop solar features such as spongy bright spots exist near coronal loops, further increasing the complexity and reducing the accuracy of loop extraction.

Current loop identification methods fall into two main categories. One approach uses intensity and gradient thresholds in the spatial domain to identify and extract features, while the other employs frequency or wavelet domain filtering to recognize and extract loop characteristics. Importantly, substantial low-level information about image structural features—such as edges, scales, and textures —is stored in the image phase spectrum. Phase congruency technology offers illumination invariance and achieves stable feature extraction by calculating local energy. This technique has been successfully applied to extract and identify low-contrast solar features including sunspot umbra dots, umbral flashes, and photospheric granulation, demonstrating that phase congruency effectively characterizes structural features regardless of intensity variations.

2. Data and Methodology

2.1 Experimental Data

This study analyzes coronal loop oscillations observed by the Solar Dynamics Observatory' s Atmospheric Imaging Assembly (AIA) in the Fe IX 17.1 nm band. The oscillation event occurred in active region AR11283, which produced an X2.1-class flare. The dataset comprises images with a pixel resolution of 0.6 and a cadence of 12 seconds. The white arrow in [Figure 1: see original paper] indicates the flare eruption site, while the white box marks the region of interest (210 $\times$ 144) where intense oscillations were triggered in nearby loops. This paper focuses on applying the proposed algorithm to identify and track the oscillations of Loop A and Loop B, which show particularly prominent oscillatory behavior.

2.2 Identification and Tracking Algorithm

The algorithm first employs the phase congruency method from references [14-15] to calculate the local weighted mean phase angle in the phase congruency map. This phase angle image has a value range of [-$\pi/2$, $\pi/2$], where the values represent positions of intensity extrema in local regions of the original image. A value of $\pi/2$ indicates features transitioning from bright to dark, while -$\pi/2$ indicates the opposite.

Figure 2: see original paper shows the phase congruency features extracted from Figure 1: see original paper. While the loop structures are identified, spongy bright spots and near-vertical features generated by the flare eruption are also detected. Since coronal loops appear as bright features in the original images, the algorithm selects a threshold of $\pi/2$ during binarization, with results shown in Figure 2: see original paper. The white box in the center of Figure 2: see original paper marks interference features that disrupt the extraction of Loops A and B.

Because the target loops A and B are nearly horizontal, the algorithm adopts directional filtering to identify and remove near-vertical features. A Sobel edge detection operator is employed as the directional filter to detect and eliminate these interfering vertical edges:

$$\text{Sobel} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Figure 2: see original paper demonstrates that the near-vertical interference features have been accurately removed through directional filtering. However, the extracted loop structures still exhibit discontinuities, small holes, irregular edges, noise, and non-uniform thickness. The algorithm addresses these issues through morphological operations including small area removal and thinning, with results shown in Figure 2: see original paper.

As seen in Figure 2: see original paper, the identified loops are not smooth and contain many branch structures. In addition to the target Loops A and B, numerous short non-target lines remain. The algorithm therefore removes short branch noise by preserving only the longest branch at each node based on branch length, successfully extracting Loops A and B as shown in Figure 2: see original paper.

Finally, quadratic curve fitting is applied to the identified loops across all images to obtain smooth curves. The quadratic equation is defined as:

$$y = ax^2 + bx + c$$

where x and y represent the horizontal and vertical coordinates of the loop in the image, and a, b, c are parameters. The fitting parameters for Loops A and B in Figure 2: see original paper are listed in . Due to oscillations causing different loop morphologies in each image, individual fitting was performed for every frame, though only representative parameters are shown. These fitted curves serve as the features for statistical analysis and are overlaid on the original images in Figure 2: see original paper.

3. Experimental Results and Analysis

To validate the identification results, five points were selected along the X-direction for both Loop A and Loop B. Using the quadratic fitting equations for each image, Y-values were calculated for these points. The mean Y-value across the five points for each image was taken as the loop' s oscillation position, yielding displacement curves over time.

Figure 3: see original paper plots time on the horizontal axis (minutes) and loop displacement on the vertical axis, with asterisks marking the mean Y-positions of Loops A and B. The pattern resembles a damped sinusoidal function, which is fitted using:

$$f(t) = Ae^{-t/\tau} \sin\left(\frac{2\pi t}{T} + \phi\right)$$

where A is amplitude, τ is decay time, T is period (minutes), and ϕ is initial phase.

The oscillation periods were determined through Fourier transform frequency analysis. The frequency spectra of both oscillation signals are shown in [Figure 4: see original paper]. The analysis reveals oscillation frequencies of approximately 8.4 mHz, corresponding to periods of about 118 seconds for both loops. However, the two oscillation sequences exhibit a phase difference of approximately 41°, with Loop B oscillating ahead of Loop A. Loop B also shows higher amplitude than Loop A. This indicates that flare-induced coronal loop oscillations do not necessarily begin in the nearest loop, but can start in more distant loops first —though this apparent distance may be influenced by viewing angle. These results are consistent with previous studies, further validating that the proposed method can be applied to coronal loop research and analysis.

4. Discussion and Conclusion

Most coronal loop oscillations are triggered by nearby flare eruptions and coronal mass ejections. Analyzing these oscillations enhances understanding of the relationship between coronal magnetic field characteristics and energy release processes in solar eruptions, making accurate loop identification crucial. This paper employed phase congruency combined with directional filtering to analyze loop oscillations observed by AIA in the 17.1 nm band.

Due to the complexity of coronal loop structures, this study focused on two prominent loops in the oscillating region, using phase congruency and directional filtering for identification and tracking. Statistical analysis of the oscillation period, phase difference, and decay coefficient for these two loops showed good agreement with previous literature, demonstrating the algorithm' s feasibility. While phase congruency effectively addresses feature extraction under low signal-to-noise conditions, some faint loops remain unidentified. In such cases, image processing alone is insufficient, and integration with multi-wavelength data and magnetic field inversion analysis is needed to improve identification accuracy. This represents the next stage of research, as the complex background, blurred loop edges, and low signal-to-noise ratio currently limit the completeness of extracted loop structures.

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Note: Figure translations are in progress. See original paper for figures.