Postprint: Solar Magnetic Field Image Registration and Localization Method Based on Scale-Invariant Feature Point Matching

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Abstract

Different solar observatories exhibit variations in observation time, coverage, and instrumentation. To facilitate scientific research, it is essential to develop methods for automatic registration and localization of solar images across different observatories. This paper proposes a method for solar magnetic field image registration and localization based on scale-invariant feature point matching. First, preprocessing operations including contrast enhancement and downsampling are applied to the original images. Second, a scale-invariant feature detection algorithm is employed to extract scale-invariant feature points from both images. Third, a correspondence point identification method is used to perform coarse registration and localization of the feature points. Finally, precise registration and localization of solar magnetic field images are achieved based on the coarsely localized regions. Experiments on magnetic field images from different time periods were conducted, with quantitative analysis performed on parameters including the number of matching point pairs, matching accuracy, and matching error. The experimental results demonstrate that the proposed method can automatically, accurately, and rapidly achieve registration and localization of solar magnetic field images.

Full Text

Preamble

Registration and Location Method of Solar Magnetic Field Images Based on Scale-Invariant Feature Point Matching

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Abstract

Differences in observation time, scope, and equipment among various solar observatories necessitate an automatic method for registering and locating solar images from different stations to facilitate scientific research. This paper proposes a registration and location method for solar magnetic field images based on scale-invariant feature point matching. The approach consists of four main steps: First, original images undergo preprocessing including contrast enhancement and downsampling. Second, scale-invariant feature points are extracted from both images using a scale-invariant feature detection algorithm. Third, homologous point matching is employed for coarse registration and initial positioning of the feature points. Finally, precise registration and localization of solar magnetic field images are achieved based on the coarsely located region. Experiments were conducted on magnetic field images from different time periods, with quantitative analysis performed on parameters including the number of matching point pairs, matching accuracy, and matching error. The results demonstrate that the proposed method can automatically, accurately, and rapidly achieve registration and localization of solar magnetic field images.

Keywords: Solar image; Image registration; Automatic positioning; Scale-invariant; Feature extraction

Introduction

Solar magnetic fields play a crucial role in solar activity. To predict eruptive events such as flares and coronal mass ejections, it is essential to monitor the magnetic and flow field structures and their evolution from the solar photosphere to the corona [?]. Currently, multiple solar magnetic field observation facilities have been established both domestically and internationally, including the 35cm Solar Magnetic Field Telescope (SMFT) at the Huairou Solar Observing Station (HSOS) in China [?] and the Helioseismic and Magnetic Imager (HMI) onboard the Solar Dynamics Observatory (SDO) [?]. Significant differences exist among different solar observatories in terms of observation time, observation scope, and observation equipment. To facilitate scientific research and improve the utilization efficiency of solar physics data, it is necessary to develop automatic registration methods for solar images from different observatories. Additionally, when the observation fields of two instruments differ, automatic localization of "small images" within "large images" is required. For example, the solar magnetic field telescope at Huairou Solar Observing Station produces local solar magnetic field images, whereas the HMI instrument on SDO provides full-disk solar magnetic field images. The observation scope of the former is far smaller than that of the latter, necessitating a method for rapidly locating local solar images within full-disk images.

Several studies have addressed solar image registration. Reference [?] proposed a subpixel solar image registration algorithm based on modified moments, while reference [?] employed an information entropy and SIFT algorithm for solar image registration. These methods focus on sequential images from the same observatory, where the imaging equipment position is fixed and image content changes minimally over short periods, with few displacement, rotation, or affine transformations. Solar images from different observatories exhibit greater differences in observation time, scope, and equipment, requiring more robust image registration methods. Numerous image registration methods exist, including intensity-based methods [?] and feature-based methods [?]. Intensity-based methods offer high accuracy but suffer from high computational complexity and sensitivity to rotation, deformation, occlusion, and intensity changes. Scale-invariant feature point matching methods [?] require less computation and demonstrate better adaptability to intensity variations, image deformation, and occlusion. Solar magnetic field images contain numerous internal structures with distinct feature points. This paper proposes a solar magnetic field image registration and localization method based on scale-invariant feature point matching. The study investigates the automatic registration and localization of local solar magnetic field images from Huairou Solar Observing Station within full-disk solar magnetic field images from SDO/HMI, and experimental tests demonstrate the method' s effectiveness.

1. Algorithm Principle

The scale-invariant feature point matching algorithm for automatic registration and localization of local solar images within full-disk solar images primarily comprises scale-invariant feature extraction, initial feature point matching, precise feature point matching, and transformation matrix calculation.

1.1.1 Scale Space Extrema Detection

Scale space theory forms the foundation for detecting invariant features. Reference [?] proved that the Gaussian convolution kernel is the unique linear kernel for scale transformation. The scale space of a two-dimensional image at different scales can be expressed as the convolution of the image with a Gaussian kernel:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y), \tag{1}$$

where (x, y) represents the pixel coordinates of an image point, $I(x, y)$ is the image intensity value, and $G(x, y, \sigma)$ is the Gaussian kernel function:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}, \tag{2}$$

where σ is the scale space factor representing the variance of the Gaussian normal distribution, reflecting the degree of image smoothing, and $L(x, y, \sigma)$ is the image scale space.

To efficiently detect stable extrema in scale space, reference [?] uses extrema of the Difference-of-Gaussian (DoG) in scale space as the detection criterion. The DoG operator is defined as:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y), \quad (3)$$

where k is the ratio factor between adjacent scale spaces.

DoG local extrema detection compares each pixel' s DoG value with 8 neighboring pixels in the same scale and 9×2 neighboring pixels in adjacent scales at corresponding positions, totaling 26 pixels. A point is considered an extremum only when its DoG value is greater than or less than all 26 neighboring pixels.

1.1.2 Determination of Keypoint Location and Scale

Keypoint locations and scales are precisely determined by fitting a three-dimensional quadratic function, yielding a set of candidate points for the scale-invariant feature extraction algorithm. Low-contrast points are sensitive to noise, while points on edges are difficult to locate accurately. To ensure the stability of scale-invariant feature points, these two types of points must be eliminated from the candidate set.

1.1.3 Keypoint Orientation Assignment

Assigning orientations to keypoints enables feature descriptors to be constructed in a rotation-dependent manner, thereby providing rotation invariance. Keypoint orientations are determined using the gradient distribution characteristics of neighboring pixels. For each Gaussian image, the gradient orientation $\theta(x, y)$ at each point $L(x, y)$ can be calculated as [?]:

$$\theta(x, y) = \tan^{-1} \frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)}. \quad (4)$$

1.1.4 Feature Vector Generation

To ensure rotation invariance of the descriptor, the coordinate system is first rotated to align with the keypoint orientation. The 360° gradient direction range is then divided into 8 directional bins, each covering 45°. With a 4×4 subregion configuration, this yields 4×4×8=128 data points, generating a 128-dimensional descriptor. The combination of orientation and spatial information not only enhances noise resistance but also eliminates the effects of scale variation, rotation, and deformation [?, ?].

1.2 Initial Feature Point Matching

After feature point detection, homologous point matching can be used for coarse matching of feature points between two images [?, ?]. Euclidean distance d serves as the similarity metric between images to determine homologous points. The two-dimensional Euclidean distance is expressed as:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}. \tag{5}$$

The process involves first identifying the two points in the image to be registered with the shortest Euclidean distances to a given extremum point in the reference image. The smaller distance is then divided by the larger distance. If this ratio falls within a given threshold range, a homologous point relationship is established, designating them as matching points. Threshold selection directly affects the number of homologous points. A larger threshold yields more matching points but potentially more false matches, while an excessively small threshold produces too few matches. Extensive experiments indicate that a threshold between 0.4 and 0.6 is optimal [?].

1.3 Precise Feature Point Matching and Transformation Matrix Calculation

After coarse matching, the Random Sample Consensus (RANSAC) algorithm [?] can eliminate incorrect matches to improve registration accuracy. RANSAC iteratively seeks the optimal parameter model from a dataset containing "outliers," with points not conforming to the optimal model defined as "outliers." Originally proposed in reference [?], this algorithm has been widely applied in image registration and stitching.

Generally, the transformation between two images can be represented by a transformation matrix [?]:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_0 & h_1 & h_2 \\ h_3 & h_4 & h_5 \\ h_6 & h_7 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix},$$

where (x', y') and (x, y) are the pixel coordinates of corresponding points in the two images, and h_i $(i = 0, 1, 2...7)$ are the eight unknown coefficients of the transformation matrix.

The RANSAC algorithm enables precise feature point matching and transformation matrix estimation. It randomly selects four corresponding point sets to form a sample and calculates the transformation matrix H. For each hypothetical correspondence, the distance d is computed. The number of inliers consistent with H is then calculated. The H with the maximum number of inliers is selected; when numbers are equal, the solution with the smallest inlier standard deviation is chosen [?]. Finally, based on the inter-image transformation matrix

H, the pixel coordinates of the four vertices and center point of the local solar image in the full-disk image can be calculated, completing the registration and localization of the local solar image within the full-disk solar image.

2. Experimental Results and Analysis

2.1 Algorithm Design

The workflow of the solar magnetic field image registration and localization method based on scale-invariant feature matching is as follows: (1) Preprocess images through downsampling, intensity inversion, and contrast enhancement, reducing images to approximately 1024×1024 pixels; (2) Extract image feature points using the scale-invariant feature extraction algorithm; (3) Perform coarse matching of feature points between the two images using homologous point matching; (4) Eliminate incorrect matches using RANSAC and estimate the optimal transformation matrix between the images; (5) Achieve initial localization of the local solar image within the full-disk solar image based on the affine transformation matrix; (6) Perform precise registration using the initially localized image region and the Huairou local image.

The specific algorithm flowchart is shown in Figure 1 [Figure 1: see original paper].

2.2.1 Registration and Localization of Solar Magnetic Field Images from Different Observatories

Experiments were conducted on the automatic matching and localization of local solar magnetic field images from Huairou Solar Observing Station within full-disk solar magnetic field images from SDO/HMI. Figure 2 [Figure 2: see original paper] presents the original full-disk and local solar images. Figure 2(a) shows the full-disk solar magnetic field image obtained by HMI [**?**], captured on November 12, 2012 at 05:48:00 UT. Figure 2(b) shows the local solar magnetic field image obtained by the 35cm Solar Magnetic Field Telescope [**?**], captured on November 12, 2012 at 05:55:34 UT. The observation times are very close. Notably, the observation scopes and resolutions differ significantly: the Huairou local solar image represents only a tiny portion of the full-disk solar image. The full-disk image dimensions are 4096×4096 pixels, while the Huairou local image dimensions are 830×992 pixels.

The contrast of the two images in Figure 2 is insufficient. Before subsequent image registration, preprocessing including contrast enhancement is necessary. Additionally, due to the high resolution of the HMI full-disk image, downsampling from 4096×4096 to 1024×1024 pixels is performed to improve registration speed. Furthermore, the polarity of some HMI full-disk solar magnetic field images is opposite to that of Huairou images, requiring intensity inversion. The preprocessed full-disk solar magnetic field image after downsampling, intensity inversion, and contrast enhancement is shown in Figure 3 Figure 3: see original paper. The preprocessed local solar image after contrast enhancement is shown in Figure 3(b). Comparing Figures 2(b) and 3(b) reveals that the preprocessed solar images are clearer than the original images, which facilitates subsequent feature extraction and image registration.

Feature points are then extracted using the scale-invariant feature extraction algorithm. Figure 4 [Figure 4: see original paper] shows the scale-invariant feature detection results for the preprocessed local solar image, with 204 feature points detected. These feature points effectively represent the characteristics of the local solar image.

After scale-invariant feature detection on both images in Figure 3, the feature points must be matched. The full-disk image contains 3,447 scale-invariant feature points, while the local solar image contains 204. Homologous point matching and RANSAC are then applied to identify corresponding feature point pairs between the two images. As shown in Figure 5 [Figure 5: see original paper], 20 matching feature point pairs were found (connected by red lines in the figure).

Based on these matched feature point pairs, the transformation matrix H_1 between the two images can be initially estimated [?], as shown in equation (7):

$$H_1 = \begin{bmatrix} -0.1375 & 0.0583 & 727.0 \\ -0.0573 & -0.1303 & 675.9 \\ 0 & 0 & 1 \end{bmatrix}. \tag{7}$$

Using transformation matrix H_1, the pixel positions of the four vertices and center point of the local image in the full-disk image can be calculated, completing coarse localization of the local image within the full-disk image (Figure 5).

While downsampling the HMI full-disk image significantly improves computational speed, it simultaneously reduces matching and localization accuracy. To address this, precise matching is performed between the minimum bounding rectangle region corresponding to the green quadrilateral in the original HMI full-disk image (see Figure 5) and the Huairou local solar image to determine the exact location of the local solar image within the full-disk image. The precise matching results are shown in Figure 6 [Figure 6: see original paper], with 25 matching feature point pairs identified (connected by red lines). Based on these matched feature point pairs, the optimal transformation matrix H_2 can be estimated, as shown in equation (8):

$$H_2 = \begin{bmatrix} -0.5425 & 0.2270 & 547.2349 \\ -0.2221 & -0.5300 & 662.1596 \\ 0 & 0 & 1 \end{bmatrix}. \tag{8}$$

From transformation matrix H_2, it is evident that the geometric transformations between the two images primarily consist of scaling, rotation, and translation, without perspective transformation. The precise positions of the four vertices of the local image in the full-disk image are calculated as (2909, 2704), (2371, 2484), (2560, 2045), and (3097, 2265) (marked by the green quadrilateral in Figure 6), completing precise localization of the local image within the full-disk image. Additionally, the rotation angle of the local solar image relative to the full-disk image is approximately 157.9° (clockwise), with a horizontal scaling factor of 1.71 and a vertical scaling factor of 1.74.

Figure 7 [Figure 7: see original paper] shows the magnified region of the full-disk solar image (Figure 7(a)) and the transformed local solar image using transformation matrix H (Figure 7(b)). The shapes and orientations of the two images are essentially consistent, though minor differences exist in details. The consistency in shape and orientation demonstrates the accuracy of the proposed algorithm. The minor differences arise because the images are obtained from different observatories with variations in observation time and telescope parameters. However, these subtle differences do not affect the registration and localization of the local solar image within the full-disk image.

2.2.2 Matching Results for Different Time Periods

To validate the algorithm' s effectiveness, registration experiments were conducted on 71 sets of solar images from different time periods. The corresponding numbers of matched point pairs and correctly matched point pairs are presented in Figure 8 [Figure 8: see original paper]. The red solid circles represent the actual number of matched point pairs, the green dashed points represent the number of correctly matched point pairs, and the blue dashed stars represent the matching accuracy rate (the ratio of correctly matched point pairs to actual matched point pairs). The full-disk image resolution is 1024×1024 pixels for all cases. Figure 8 shows that in most cases, the number of correctly matched point pairs equals the actual number of matched point pairs, yielding 100% matching accuracy. In a few cases, the number of correctly matched point pairs is less than the actual number, indicating some false matches. False matches occur because the Huairou local solar image is ground-based while the HMI full-disk solar image is space-based. Under atmospheric turbulence interference, the Huairou local solar image becomes blurred, reducing the number of feature points detectable by the SIFT algorithm and consequently decreasing the number of matched point pairs and matching accuracy. Figure 9 [Figure 9: see original paper] shows the registration results when the local solar image is relatively blurred, with lower numbers of matched point pairs and matching accuracy.

2.2.3 Effect of Affine Transformation on Solar Magnetic Field Image Registration

In addition to common scaling, rotation, and translation transformations, solar magnetic field images from different observatories often exhibit noticeable affine transformations. This section investigates the effect of affine transformation on solar magnetic field image registration results through quantitative analysis and calculation of registration errors. A rectangular sub-image is extracted from the original HMI full-disk image (Figure 2(a)). The sub-image is then subjected to specific affine transformations and registered with the downsampled full-disk image (Figure 3(a)). The registration error is accurately calculated by subtracting the known positions of the sub-image' s four vertices in the full-disk image from the positions predicted by the transformation matrix.

The registration error η is defined as:

$$\eta = \frac{1}{4}\sum_{i=0}^{3}\sqrt{(x_i - x_i^0)^2 + (y_i - y_i^0)^2}, \tag{9}$$

where (x_i^0, y_i^0) and (x_i, y_i) are the known and predicted positions of the sub-image' s four vertices in the full-disk image, respectively.

Affine transformation includes translation, rotation, scaling, and shearing. Figure 10 [Figure 10: see original paper] shows the variation of registration error (in pixels) with shear coefficient and rotation angle at a scaling factor of 0.6. The results indicate that registration error remains small for small shear coefficients but increases rapidly when the shear coefficient exceeds approximately 0.3. Rotation angle has minimal impact on registration results. Figure 11 [Figure 11: see original paper] shows the variation of registration error with shear coefficient and scaling factor at a rotation angle of 45°. The results demonstrate that scaling has minimal impact on registration error within a factor of 2, but error increases significantly beyond this range. This occurs because downsampling discards image information while upsampling requires interpolation. When downsampling discards too much information or upsampling introduces excessive interpolation, feature point detection and matching are adversely affected. In summary, the SIFT registration algorithm employed in this paper demonstrates robustness to rotation, scaling, and shearing transformations. To better reflect the impact of affine transformation on registration accuracy, the results in this section were obtained through initial localization (corresponding to algorithm steps a-e). Precise localization can substantially reduce registration error.

3. Conclusion

This study investigated the registration and localization of local solar magnetic field images from Huairou Observing Station within full-disk images from SDO/HMI using a scale-invariant feature point matching method. The results demonstrate that the algorithm exhibits strong robustness to illumination, rotation, and scale variation, and is effective for registering solar magnetic field images obtained under different observation conditions and scales from different observatories, thereby improving the utilization efficiency of solar physics data.

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