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

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Abstract

Different solar observatories exhibit variations in observation time, observation range, and observation equipment. To facilitate scientific research, it is necessary 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 such as contrast enhancement and downsampling are performed on the original images. Second, a scale-invariant feature detection algorithm is employed to extract scale-invariant feature points from both images. Then, a method for finding corresponding points is utilized to conduct coarse registration and coarse localization of the feature points between the two images. Finally, precise registration and localization of the solar magnetic field images are achieved based on the coarsely localized regions. Experiments on registration and localization of 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

Solar observation stations differ in observation time, field of view, and equipment. To facilitate scientific research, it is necessary to develop a method for automatic registration and localization of solar images across different stations. This paper proposes a solar magnetic field image registration and localization method based on scale-invariant feature point matching. The approach consists of four main steps: First, preprocessing operations including contrast enhancement and downsampling are applied to the original images. Second, a scale-invariant feature detection algorithm extracts feature points from both images. Third, a coarse registration and localization is performed by identifying homologous points between the two feature sets. Finally, precise registration and localization of solar magnetic field images is 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 registration 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 localization; scale-invariant; feature extraction

Introduction

Solar magnetic fields play a crucial role in solar activity. Monitoring the magnetic and flow field structures and their evolution from the photosphere to the corona is essential for predicting eruptive events such as flares and coronal mass ejections [1]. Currently, numerous 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 [2] and the Helioseismic and Magnetic Imager (HMI) on the Solar Dynamics Observatory (SDO) [3]. However, different solar observation stations exhibit significant differences in observation time, field of view, and 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 across different stations. Additionally, when the observation fields differ between two instruments, automatic localization of "small images" within "large images" is required. For instance, the solar magnetic field telescope at HSOS produces local solar magnetic field images, whereas SDO/HMI provides full-disk solar magnetic field images. The former's observation range is substantially smaller than the latter's, necessitating a method for rapid automatic localization of local solar images within full-disk images.

Several studies have addressed solar image registration. For example, reference [4] proposed a subpixel solar image registration algorithm based on modified moments, while reference [5] employed an information entropy and SIFT algorithm for solar image registration. However, these methods target sequential images from the same observation station where the imaging equipment is fixed and image content changes minimally over short periods, with limited displacement, rotation, and affine transformations. Solar images from different stations exhibit greater variations in observation time, field of view, and equipment, requiring more robust registration methods. Numerous image registration methods exist, including intensity-based approaches [6-7] and feature-based methods [8-9]. Intensity-based methods offer high precision but suffer from high computational complexity and sensitivity to rotation, deformation, occlusion, and intensity changes. In contrast, scale-invariant feature point matching methods [10-11] involve 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, investigating the automatic registration and localization of local solar magnetic field images from HSOS within full-disk solar magnetic field images from SDO/HMI, and demonstrating the method' s effectiveness through experimental verification.

1. Algorithm Principle

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

1.1 Scale-Invariant Feature Extraction

1.1.1 Scale Space Extrema Detection Scale space theory forms the foundation for detecting invariant features. Reference [12] proved that the Gaussian convolution kernel is the only transformation kernel for scale changes. The scale space representation of a two-dimensional image at different scales can be expressed as the convolution of the image with a Gaussian kernel:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

where (x, y) represents pixel coordinates, $I(x, y)$ denotes image intensity values, and $G(x, y, \sigma)$ is the Gaussian kernel function:

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

In these equations, σ is the scale space factor representing the variance of the Gaussian normal distribution, which reflects the degree of image smoothing. $L(x, y, \sigma)$ constitutes the image' s scale space.

To efficiently detect stable extrema in scale space, reference [10] employs extrema of the Difference-of-Gaussian (DoG) in scale space as the detection criterion. The DoG operator is defined as:

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

where k is the ratio factor between adjacent scale spaces. DoG local extrema detection compares each pixel' s DoG value with its 8 neighboring pixels in the same scale and 9×2 neighboring pixels in adjacent scales, totaling 26 pixels. A point is identified as an extremum only when its DoG value is greater than or less than all 26 neighboring pixels, and is then preserved for subsequent calculations.

1.1.2 Keypoint Localization and Scale Determination The precise location and scale of keypoints are determined by fitting a three-dimensional quadratic function, yielding a candidate set of SIFT feature points. However, low-contrast points are sensitive to noise, while points on edges are difficult to localize accurately. To ensure the stability of SIFT feature points, these two types of points must be eliminated from the candidate set.

1.1.3 Keypoint Orientation Assignment Assigning orientation to keypoints enables the construction of feature descriptors in a rotation-dependent manner, thereby conferring rotation invariance to the operator. Keypoint orientation is determined using the gradient distribution characteristics of neighboring pixels. For each Gaussian image, the gradient magnitude $m(x, y)$ and orientation $\theta(x, y)$ at each point $L(x, y)$ can be calculated as [10]:

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2}$$

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

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 orientation 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 location information not only enhances noise resistance but also eliminates the effects of scale changes, rotation, and deformation [5,10].

1.2 Initial Feature Point Matching

Following feature point detection, initial coarse matching between feature points in the two images can be performed using a homologous point detection method [5,10]. Euclidean distance d serves as the similarity metric to identify corresponding points. The two-dimensional Euclidean distance is expressed as:

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

The process involves first identifying the two points in the target image with the shortest Euclidean distances to a given extremum point in the reference image. The smaller distance is then divided by the larger distance, and if this ratio falls within a specified threshold range, a homologous point relationship is established, designating them as matching points. Threshold selection directly affects the number of homologous points: larger thresholds yield more matches but increase potential false matches, while overly small thresholds produce insufficient matches. Extensive experiments indicate that thresholds between 0.4 and 0.6 perform optimally [5].

1.3 Precise Feature Point Matching and Transformation Matrix Calculation

After coarse matching, the Random Sample Consensus (RANSAC) algorithm [9] can eliminate erroneous matches to improve registration accuracy. RANSAC iteratively searches for the optimal parameter model within a dataset containing "outliers," with points not conforming to the optimal model defined as outliers. Originally proposed in reference [9], this algorithm has been widely applied in image registration and stitching.

Generally, the transformation between two images can be represented by a transformation matrix [13]:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} h_0 & h_1 & h_2 \\ h_3 & h_4 & h_5 \\ h_6 & h_7 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \quad (6)$$

where (x', y') and (x, y) are corresponding pixel coordinates 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 algorithm then counts the number of inliers consistent with H, selecting the solution with the maximum number of inliers. When inlier counts are equal, the solution with the smallest inlier standard deviation is chosen [13]. Finally, based on the transformation matrix H between images, the pixel coordinates of the four vertices and center point of the local solar image within the full-disk image can be calculated, completing the registration and localization process.

2. Experimental Results and Analysis

2.1 Algorithm Design

The workflow for the proposed 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 SIFT algorithm; (3) Perform coarse matching of feature points between the two images using the homologous point method; (4) Apply RANSAC to eliminate false matches and estimate the optimal transformation matrix between images; (5) Achieve preliminary localization of the local solar image within the full-disk image based on the affine transformation matrix; (6) Perform precise registration using the preliminarily localized region and the Huairou local image. The detailed algorithm flowchart is shown in [Figure 1: see original paper].

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

Experiments were conducted on automatic matching and localization of local solar magnetic field images from HSOS within full-disk solar magnetic field images from SDO/HMI. [Figure 2: see original paper] presents the original full-disk and local solar images. Figure 2: see original paper shows the full-disk solar magnetic field image obtained by HMI [3], captured on November 12, 2012 at 05:48:00 UT. Figure 2: see original paper displays the local solar magnetic field image from the 35cm SMFT [2], captured on November 12, 2012 at 05:55:34 UT. The observation times are very close, but the fields of view and resolutions differ significantly—the HSOS local image represents only a small portion of the full-disk image, with dimensions of 830×992 pixels compared to the full-disk image' s 4096×4096 pixels.

The contrast in both [Figure 2: see original paper] images is insufficient, necessitating preprocessing through contrast enhancement before registration. Additionally, due to the high resolution of SDO/HMI full-disk images, downsampling from 4096×4096 to 1024×1024 pixels was performed to improve registration speed. Furthermore, the polarity of some SDO/HMI full-disk solar magnetic field images is opposite to that of HSOS images, requiring intensity inversion. The preprocessed full-disk solar magnetic field image after downsampling, intensity inversion, and contrast enhancement is shown in Figure 3: see original paper, while the contrast-enhanced local solar image appears in Figure 3: see original paper. Comparison between Figure 2: see original paper and Figure 3: see original paper reveals that preprocessed images are clearer than originals, facilitating subsequent feature extraction and registration.

Subsequently, the SIFT algorithm extracted image feature points. [Figure 4: see original paper] shows the SIFT detection results for the preprocessed local solar image, identifying 204 feature points that effectively represent the local solar image characteristics. After SIFT detection on both images in [Figure 3: see original paper], feature point registration was performed. The full-disk image yielded 3,447 feature points, while the local image produced 204. The homologous point method and RANSAC algorithm were then applied to identify matching feature pairs. As shown in [Figure 5: see original paper], 20 matching feature pairs were found (connected by red lines). Based on these pairs, the initial transformation matrix H_1 [13] was estimated as:

$$H_1 = \begin{pmatrix} 1.71 & -0.02 & 2371.5 \\ 0.02 & 1.74 & 2045.3 \\ 0 & 0 & 1 \end{pmatrix} \quad (7)$$

This matrix calculated the pixel positions of the local image' s four vertices and center point within the full-disk image, completing coarse localization ([Figure 5: see original paper]).

While downsampling SDO/HMI full-disk images significantly improves computational speed, it reduces matching and localization accuracy. Therefore, precise matching was performed between the minimum bounding rectangle region corresponding to the green quadrilateral in the original SDO/HMI full-disk image ([Figure 5: see original paper]) and the HSOS local solar image to determine the exact location. The precise matching results are shown in [Figure 6: see original paper], identifying 25 matching feature pairs (connected by red lines). The optimal transformation matrix H_2 was estimated as:

$$H_2 = \begin{pmatrix} 1.71 & -0.02 & 2371.5 \\ 0.02 & 1.74 & 2045.3 \\ 0 & 0 & 1 \end{pmatrix} \quad (8)$$

The transformation matrix H_2 indicates that the geometric transformations between images primarily involve scaling, rotation, and translation without perspective transformation. The precise positions of the local image' s four vertices within the full-disk image were calculated as (2909, 2704), (2371, 2484), (2560, 2045), and (3097, 2265) (marked by the green quadrilateral in [Figure 6: see original paper]), completing precise localization. Additionally, the local solar image' s rotation angle relative to the full-disk image was approximately 157.9° (clockwise), with horizontal and vertical scaling factors of 1.71 and 1.74, respectively.

[Figure 7: see original paper] presents magnified views of the full-disk solar magnetic field image (Figure 7: see original paper) and the transformed local solar magnetic field image (Figure 7: see original paper). The shapes and orientations of both images are essentially consistent, though minor differences exist in details. The consistency in shape and orientation validates the algorithm' s accuracy. The slight discrepancies arise because the images originate from different observatories with differences in observation time and telescope parameters, but these minor variations do not affect the registration and localization of local solar images within full-disk images.

2.2.2 Matching Results Across Different Time Periods

To validate the algorithm' s effectiveness, registration experiments were conducted on 71 groups of solar images from different time periods. [Figure 8: see original paper] shows the corresponding numbers of matching point pairs and correctly matched pairs. The red solid circles represent actual matching point pairs, green dashed points indicate correctly matched pairs, and blue dashed stars show matching accuracy (ratio of correctly matched pairs to actual pairs). All full-disk images were at 1024×1024 resolution. [Figure 8: see original paper] demonstrates that in most cases, the number of correctly matched pairs equals the actual number of pairs, yielding 100% accuracy. In 少数 cases, correctly matched pairs are fewer than actual pairs, indicating some false matches. These errors occur because the HSOS local solar images are ground-based while SDO/HMI full-disk images are space-based. Atmospheric turbulence and other disturbances blur the HSOS images, reducing the number of feature points detectable by SIFT and consequently decreasing both the number of matching pairs and registration accuracy. [Figure 9: see original paper] illustrates registration results when the local solar image is relatively blurry, showing reduced matching pairs and accuracy.

2.2.3 Impact of Affine Transformations on Registration Results

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 impact of affine transformations on registration results through quantitative error analysis. A rectangular subimage was extracted from the original SDO/HMI full-disk image (Figure 2: see original paper), subjected to specific affine transformations, and then registered with the downsampled full-disk image (Figure 3: see original paper). Registration error was accurately calculated by subtracting the known positions of the sub-image' s vertices within the full-disk image from the positions predicted by the transformation matrix. Registration error h is defined as:

$$h = \frac{1}{4}\sum_{i=1}^{4}\sqrt{(x_i - x_i')^2 + (y_i - y_i')^2} \quad (9)$$

where (x_i, y_i) and (x_i', y_i') represent the known and predicted positions of the sub-image' s four vertices within the full-disk image, respectively.

Affine transformations include translation, rotation, scaling, and shearing. [Figure 10: see original paper] shows registration error (in pixels) as a function of 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: see original paper] illustrates registration error as a function of shear coefficient and scaling factor at a rotation angle of 45°. Scaling within a factor of 2 (either up or down) has minimal impact on registration error, but error increases significantly beyond this range because downsampling discards image information while upsampling requires interpolation. When too much information is discarded during downsampling or excessive interpolation occurs during upsampling, feature detection and registration 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 transformations on registration accuracy, the results in this section were obtained through preliminary localization (corresponding to algorithm steps a-e), and precise localization can substantially reduce registration error.

3. Conclusion

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

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