High-Precision Registration Method for High-Resolution Solar Observation Images and Full-Disk Images Postprint

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Abstract

In solar observation research, the registration of high-resolution images and full-disk images is a highly meaningful task; however, due to the existence of rotation, scaling, and translation between them, achieving high-precision matching is challenging. This paper proposes an image registration method that combines local statistical information with control point matching. The core idea involves dividing the field of view into numerous overlapping local regions at equal intervals, finding corresponding local regions on the full-disk image through correlation matching, and then calculating the sub-pixel offset between each pair of local regions. Based on these offsets, the coordinate positions of each pair of feature points are determined and used as feature control points in point matching. Finally, transformation equations for affine transformation are established based on the control points, and the least squares method is employed to solve for the transformation parameters of the entire field of view. The images are then re-iterated based on the solved parameters until convergence is achieved, completing the registration. By registering high-resolution observation images with full-disk SDO/HMI continuum images, the deviation of the fitting results is within 0.25 arcseconds.

Full Text

High-accuracy Registration Method for Solar High-resolution Observation Images and Full-disk Solar Images

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Abstract: In solar observation research, registering high-resolution images with full-disk solar images is highly significant yet challenging due to rotation, scaling, and translation differences between them. This paper proposes an image registration method that combines local statistical information with control point matching. The core idea involves dividing the field of view into numerous overlapping local regions at equal intervals, finding corresponding local regions on the full-disk image through correlation matching, and calculating sub-pixel offsets between each pair of local regions. These offset values determine the coordinate positions of feature points, which serve as control points for point matching. Finally, affine transformation equations are established based on these control points, and the transformation parameters for the entire field of view are solved using least squares. The images are then iteratively re-registered according to the solved parameters until convergence is achieved. By registering high-resolution observation images with full-disk SDO/HMI continuum images, the deviation of fitting results is within 0.25 arcseconds.

Keywords: Solar Image Registration; High-resolution Image; Full-disk Solar Images

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In solar image observation data analysis, it is often necessary to compare observations from different instruments to leverage their respective advantages across different wavelength bands, fields of view, and resolutions. Solar optical imaging observations include two categories: full-disk and high-resolution observations. For full-disk images, since the Sun' s geometric dimensions and motion patterns are known (e.g., solar radius, P-angle, rotation), various observation devices calibrate their data to a standard solar coordinate system after preprocessing. However, for local high-resolution images, pointing errors, field-of-view rotation, and focal length variations make it imprecise to determine accurate solar field coordinates directly from instrument parameters alone. Therefore, conversion must rely on similar solar structures in the images (e.g., photospheric features to photospheric features, chromospheric features to chromospheric features), i.e., field-of-view matching.

Full-disk observations have a field of view greater than 31 arcminutes, but the highest pixel resolution is only 0.5 arcseconds (Solar Dynamics Observatory/Helioseismic and Magnetic Imager, SDO/HMI). In contrast, ground-based high-resolution observations, such as China' s 1m New Vacuum Solar Telescope (NVST) and the New Solar Telescope (NST) at Big Bear Solar Observatory, have fields of view of only 1-2 arcminutes but achieve pixel resolutions of 0.05 arcseconds or better. This requires registering images with a tenfold difference in spatial resolution. Even without considering other distortions, four parameters must be obtained for local images: field rotation (R), scale (S), and center coordinates (Tx, Ty).

Image registration refers to the process of matching two or more images of the same scene obtained at different times or under different conditions and located in different coordinate systems. Due to various circumstances, multiple images of the same scene exhibit differences in resolution, position, scale, imaging mode, etc. Image registration aims to find an optimal geometric transformation solution that aligns corresponding points or at least meaningful points on the images. Currently, common registration methods in the field include feature-based point matching methods, which construct descriptors based on feature points or salient features in the image to determine matching points, then establish transformation equations for registration. Theoretically, this method can effectively solve geometric transformations such as rotation, scaling, and translation between two images if there are sufficient and sufficiently accurate control points. However, the key challenge lies in determining these points, which has been extensively studied in image processing, including Harris corners and derived Harris-Laplace methods, Scale-Invariant Feature Transform (SIFT) and derived PCA-SIFT algorithms, local feature descriptors, Very Fast SIFT (VF-SIFT), Speeded Up Robust Features (SURF), etc. Another category is region-based statistical registration methods, which primarily measure image similarity through statistical information of image regions, such as mutual information, cross-correlation functions, template matching, invariant moments, and correlation matching. Generally, these methods mainly address translation between images. For images with rotation and scaling, frequency-domain phase correlation techniques and Fourier-Mellin transforms have been developed.

However, solar observation images differ significantly from ordinary natural images. Their feature boundaries are unclear, structures are relatively blurred with considerable noise, and they have large dynamic ranges and rapid motion, with most phenomena being non-rigid motion. Solar images are generally large, with small effective targets and lack effective texture, exhibiting no obvious gradient changes. Additionally, due to uncertainties in solar imaging equipment and processes, captured solar images also exhibit rotation, scaling, and translation, with spatial resolutions often at different scales. This makes determining feature correspondence points extremely difficult. For a long time, field alignment for solar time-series images from the same observation device has employed correlation-based statistical registration, while image registration between different observation devices has remained at the stage of using prominent solar features such as sunspots, pores, and large granules to construct corresponding points. However, these feature points are few in number, have irregular structures, cannot guarantee positional measurement accuracy, and are difficult to automate using computer technology.

These problems become particularly prominent when registering high-resolution local images to full-disk images. On the other hand, through telescope mechanics and terminal optical systems, preliminary estimates of local solar image pointing, scale, and position can be obtained, though these values are not very precise and vary with time. Therefore, the practical challenge is how to improve registration accuracy and achieve fine image matching.

To address these issues, this paper proposes a solar image registration algorithm combining statistical information and correlation point matching to solve the problem of high-precision coordinate conversion between local high-resolution observation data and full-disk data at different spatial resolutions. This includes measuring image orientation angle, pixel scale, and image center position on the full-disk image. The basic idea is to first perform preliminary matching, then divide the field of view into numerous overlapping local regions to replace control points in point matching. Sub-pixel displacements between corresponding regions are determined through statistical correlation matching, thereby establishing the positions of feature point pairs in the same coordinate system. Finally, least squares iteration is used to solve the entire field' s conversion parameters, gradually improving fitting accuracy through iteration. This method successfully matches TiO observation data from the 1m Solar Telescope and New Solar Telescope with nearly simultaneous (maximum interval 11 seconds) SDO/HMI continuum images, achieving fitting result deviations within 0.25 arcseconds.

1. Experimental Data Sources

The full-disk images used in this experiment are continuum full-disk images collected by the Helioseismic and Magnetic Imager (HMI) on the Solar Dynamics Observatory (SDO), while the high-resolution images are TiO photospheric images from the 1m Solar Telescope and New Solar Telescope. The SDO/HMI instrument has a spatial resolution of approximately 0.5043 arcseconds/pixel with image dimensions of 4096 $\times$ 4096 pixels. The 1m Solar Telescope and New Solar Telescope have pixel scales of 0.04 arcseconds/pixel and 0.03 arcseconds/pixel, respectively.

[Figure 1: see original paper] (a) shows TiO observation data from the 1m Solar Telescope, observed on 2013-07-15 at 07:29:09, with an effective region size of 2304 $\times$ 1920 pixels. [Figure 1: see original paper] (b) shows SDO/HMI continuum observation data from 2013-07-15 at 07:29:15, where the red box marks the approximate position of the 1m Solar Telescope' s field of view within SDO/HMI. This paper primarily uses the matching of these images to illustrate the algorithm flow.

2.1 Registration Method Flow

The main flow of the registration method is shown in [Figure 2: see original paper]. The algorithm can be described in the following 11 steps:

(1) Perform preliminary estimation of the 1m Solar Telescope image' s orientation, scale, and position to obtain Rotation, Scaling, and Translation parameters (hereinafter referred to as RST parameters).

(2) Based on the RST parameters, rotate the SDO/HMI full-disk image and extract a sub-image from SDO/HMI with the same field of view as the 1m Solar Telescope image.

(3) According to the RST parameters and SDO/HMI' s pixel scale, downsample the 1m Solar Telescope image to the same scale as SDO/HMI.

(4) Apply Gaussian smoothing to the downsampled 1m Solar Telescope image to reduce frequency aliasing during sampling. The smoothed, downsampled 1m Solar Telescope image is denoted as S.

(5) Divide image S into N equally spaced overlapping sub-blocks, with each sub-block denoted as S_i.

(6) For each sub-block S_i and SDO/HMI sub-image R_f, use normalized cross-correlation to find each corresponding R_{f_i}.

(7) For each pair S_i and R_{f_i}, measure their sub-pixel offset and set the sub-block center as a pair of corresponding control points.

(8) Screen each control point pair, eliminating points where the distance between control points exceeds a certain pixel threshold.

(9) Establish affine transformation equations based on the remaining control points and solve for RST parameters using least squares.

(10) Calculate residuals and iteration count; if either condition is satisfied, stop iteration. Otherwise, return to step (2) and reprocess SDO/HMI and the 1m Solar Telescope image based on the RST parameters solved in step (9).

(11) Obtain the final RST parameters after iteration completion and perform registration.

Among these steps, (6) through (9) constitute the core of the algorithm, which is described in more detail below. Note that after iteration begins, the RST parameters in steps (2) to (3) are updated for each subsequent iteration based on the previous iteration' s results, meaning the algorithm reapplies smoothing to the images.

2.2 Determining Feature Control Points Through Sub-blocking

Let I be the image to be matched and R be the reference image. Divide I into N feature regions, denoted as set $\{I_i^R\}, i = 1, 2, ..., N$, where each region I_i^R has dimensions $U \times V$. The cross-correlation function between reference image R and image I is:

$$Corr(x,y) = \frac{\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[I(x+s,y+t)-\bar{I}_s\right]\left[f_R^i(s,t)-\bar{f}_R^i\right]}{\sqrt{\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[I(x+s,y+t)-\bar{I}_s\right]^2\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[f_R^i(s,t)-\bar{f}_R^i\right]^2}}$$

where $\bar{f}_R^i$ and $\bar{I}_s$ represent the mean values of the areas covered by f_R^i and I_s, respectively, and the summation is over the $u \times v$ area covered by f_R^i and I_s.

Based on the above formula, normalized cross-correlation between each I_i^R and R_f yields a correlation surface, where the peak coordinates represent the integer-pixel matching position of the I_i^R image center in R_f.

From R_f, a feature region of the same size as I_i^R can be extracted at the above position, obtaining each corresponding $I_{S_i}^f$. The set composed of them is denoted as $\{I_{S_i}^f\}, i = 1, 2, ..., N$.

For two corresponding feature regions I_i^R and $I_{S_i}^f$, use set F_i to describe the relationship between any two feature regions of I_i^R and $I_{S_i}^f$, i.e., $F_i = (I_i^R, I_{S_i}^f), i = 1, 2, ..., N$, where F_i represents any pair of corresponding local feature regions.

For each pair of feature regions $(I_i^R, I_{S_i}^f)$, compute the standard cross-correlation function. Assume D_i is the local region around the peak of the cross-correlation function distribution for feature region pair $(I_i^R, I_{S_i}^f)$. The centroid coordinates are calculated using the modified moment method:

$$(x_c, y_c) = \left(\frac{\sum_{(m,n)\in D_i} m \cdot I(m,n)}{\sum_{(m,n)\in D_i} I(m,n)}, \frac{\sum_{(m,n)\in D_i} n \cdot I(m,n)}{\sum_{(m,n)\in D_i} I(m,n)} \right)$$

where $I(m,n)$ represents the surface intensity values. The local centroid coordinates of the cross-correlation function between images represent the sub-pixel offset between each pair of feature regions.

Based on the sub-pixel offset, the coordinates corresponding to the center points of each pair of images can be established, yielding N pairs of coordinate transformation control points between I and R. Use set P to describe the relationship between control point pairs, i.e., $P_i = (p_i^R, p_i^S), i = 1, 2, ..., N$.

2.3 Solving Transformation Parameters Using Least Squares

Considering translation, rotation, and scaling, assume control point pair (p_i^R, p_i^S) with corresponding coordinates (x_A, y_A) and (x_B, y_B). The transformation relationship is:

$$\begin{bmatrix} x_B \\ y_B \end{bmatrix} = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} + (1+m) \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_A \\ y_A \end{bmatrix}$$

Converted to matrix form:

$$\begin{bmatrix} x_B - x_A \\ y_B - y_A \end{bmatrix} = \begin{bmatrix} 1 & 0 & -x_A & -y_A \\ 0 & 1 & y_A & -x_A \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ m\cos\theta - m\sin\theta \\ m\sin\theta + m\cos\theta \end{bmatrix}$$

The error equation is:

$$V = \begin{bmatrix} x_B \\ y_B \end{bmatrix} - \begin{bmatrix} 1 & 0 & -x_A & -y_A \\ 0 & 1 & y_A & -x_A \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ a \\ b \end{bmatrix}$$

where $\begin{bmatrix} x_A \\ y_A \end{bmatrix}$ are pre-transformation coordinates; $\begin{bmatrix} x_B \\ y_B \end{bmatrix}$ are post-transformation coordinates; $\begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$ are translation parameters; $(1+m)$ is the scaling parameter; and θ is the rotation parameter. Theoretically, with two pairs of control points, a set of four transformation parameters can be solved by simultaneous equations. With three or more control points, the four parameters can be solved using least squares: $T = (X, Y, m, \theta)$, where X, Y are translation parameters and m, θ are scaling and rotation parameters. The image to be matched is then transformed to the reference image.

Note that during field-of-view planar coordinate transformation, mis-matched point pairs must be screened by calculating distances between control points. In practice, if the distance between control points exceeds 5 pixels (2.5 arcseconds), the pair is considered mismatched and eliminated. Based on RST parameters solved from the screened control points, SDO/HMI and the 1m Solar Telescope images undergo RST iteration to compute the final RST transformation parameters after iteration completion.

3. Experimental Results and Analysis

In this experiment, sub-block size was set to 30×30 pixels with a block interval of 5 pixels. [Figure 3: see original paper] shows the comparison of overlapping regions after registering the 1m Solar Telescope high-resolution image with the SDO/HMI full-disk solar image. From [Figure 3: see original paper], we can see that after registration, corresponding regions of the images are completely matched except for obvious differences in clarity.

To better observe the registration effect, the registered region was overlaid and boundary areas were magnified, as shown in [Figure 4: see original paper]. The boundary details exhibit good matching, with pores, granules, and intergranular lanes connecting well.

Based on the registration results and SDO/HMI standard parameters, shows the calculated P-angle and pixel scale of this 1m Solar Telescope image, as well as the field center position in the SDO/HMI full-disk image.

TABLE:1 Registration Results

P-angle	Pixel Scale (arcsecond/pixel)	Full-disk X-coordinate	Full-disk Y-coordinate	Number of Matched Points	RMS Residual (SDO pixels)
-12.95°	0.0834	2048.31	2048.31	1247	0.31

From , the average residual is 0.31 SDO/HMI pixels, meaning the fitting result deviation is approximately 0.15 arcseconds.

[Figure 5: see original paper] shows the spatial distribution of these residuals. The residual distribution is not completely random, indicating that the 1m Solar Telescope image has distortions. This is because after reconstruction, ground-based high-resolution observation images still contain some low-frequency atmospheric jitter residuals that cannot be eliminated, limiting the final fitting accuracy. Additionally, since the observation times of the two images are not perfectly synchronized (with a 6-second interval), some solar features have already changed.

Multiple high-resolution images from the 1m Solar Telescope and New Solar Telescope were matched with SDO/HMI full-disk images, with results shown in .

TABLE:2 Registration Results of TiO Images (New Solar Telescope and 1m Solar Telescope) with SDO/HMI Full-disk Solar Images

High-resolution Image Observation Time	Time Difference with SDO/HMI (s)	RMS Residual (SDO pixels)
New Solar Telescope 2014-08-05 22:29:59	6	0.45
New Solar Telescope 2014-08-05 16:50:13	8	0.48
New Solar Telescope 2014-08-01 16:53:16	5	0.42
New Solar Telescope 2012-07-05 16:36:28	7	0.38
1m Solar Telescope 2013-07-15 07:29:09	6	0.31
1m Solar Telescope 2012-10-29 06:03:37	11	0.50

High-resolution Image Observation Time	Time Difference with SDO/HMI (s)	RMS Residual (SDO pixels)
1m Solar Telescope 2013-06-12 07:45:34	9	0.47

From the above results, the maximum matching residual is approximately 0.5 pixels, equivalent to 0.25 arcseconds.

During the experiments, we found that different parameter selections affect the algorithm, as specifically shown in [Figure 6: see original paper] through [Figure 8: see original paper].

[Figure 6: see original paper] shows the effect of initial parameter estimation on iteration count. In [Figure 6: see original paper], triangles (green), hollow circles (blue), asterisks (red), and crosses (black) represent iteration processes with estimated angles of 30°, 35°, 40°, and 45°, respectively. As initial value error increases, the algorithm requires more iterations to correct errors and converge to a reasonable range. When the initial estimated angle reaches 45° (error approximately 30°), iteration count increases from 6 to 42 for convergence.

[Figure 7: see original paper] shows the effect of control point screening distance settings on algorithm convergence speed. In [Figure 7: see original paper], crosses (red) and hollow circles (black) represent iteration processes with screening thresholds of 5 pixels and 10 pixels, respectively. When initial error is large, higher thresholds require fewer iterations, meaning faster convergence, while lower thresholds are more effective otherwise. With angle error around 30°, different thresholds differ by 28 iterations, favoring higher thresholds. With angle error around 10°, the difference is only 9 iterations, favoring lower thresholds.

[Figure 8: see original paper] shows the effect of different smoothing parameters on iteration count. In [Figure 8: see original paper], asterisks (green), hollow circles (blue), and crosses (red) represent iteration processes with smoothing parameters of 0.5, 1, and 1.5, respectively. Larger smoothing parameters increase iteration count and reduce fitting results. When the smoothing parameter is 0.5, the algorithm achieves convergence with fewer iterations and better results compared to other cases.

This paper proposes a field-of-view matching algorithm for solar high-resolution and full-disk images, solving the problem of registering solar observation images with different spatial resolutions and rotation angles. The algorithm combines regional correlation matching with control point least squares solving. Field-of-view matching experiments with high-resolution images from the 1m Solar Telescope and New Solar Telescope with SDO/HMI full-disk images demonstrate that fitting result deviations are better than 0.25 arcseconds. Through matching, the P-angle and pixel scale of high-resolution images can be precisely measured.

This method requires computing numerous small region correlations while performing iterative calculations, resulting in significant time overhead. The impact of different parameters on iteration count must be noted during application. Additionally, small sub-block sizes increase matching points and computational load while decreasing fitting accuracy; larger sizes improve accuracy but reduce matching regions, affecting overall image registration effectiveness. Sub-block interval primarily affects computation speed. Based on practical considerations, we believe sub-block size around 30 pixels with a 5-pixel interval provides reasonable algorithm stability. Parameters can be adjusted according to actual conditions in application.

Furthermore, high-precision matching of high-resolution TiO images with SDO/HMI full-disk continuum images means they can be matched with any standard full-disk images, such as SDO/HMI magnetograms, SDO/AIA observations at various wavelengths, and even chromospheric full-disk images. This enables studying the correspondence of small-scale structures across different wavelength bands and magnetic fields within 0.25 arcsecond deviation.

This scheme can be applied to any solar image registration with similar image structures, such as TiO and G-band, H wing, 10830 Å; it can also be used for registering H line-center images with GONG full-disk images. Therefore, it has numerous application prospects.

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