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

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Abstract

In solar observation research, registering high-resolution images with full-disk images is of great significance, yet high-precision matching is challenging due to rotation, scaling, and translation between them. This paper proposes an image registration method combining local statistical information with control point matching. The core idea is to divide the field of view into numerous equally-spaced, overlapping local regions, find corresponding local regions on the full-disk image through correlation matching, calculate sub-pixel offsets between each pair of local regions, and determine coordinate positions for each pair of feature points based on these offsets to serve as feature control points. Subsequently, affine transformation equations are established from these control points, and transformation parameters for the entire field of view are solved using least squares. Images are then re-iterated according to the solved parameters until convergence, completing the registration. Application to registering high-resolution observation images with full-disk SDO/HMI continuum images yields fitting deviations within 0.25 arcseconds.

Full Text

High-Accuracy Registration Method for Solar High-Resolution Observation Images and Full-Disk 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 is to divide the field of view into numerous overlapping local regions at regular intervals, find corresponding local regions on the full-disk image through correlation matching, calculate sub-pixel offsets between each pair of local regions, determine the coordinate positions of each pair of feature points based on these offsets to serve as feature control points for point matching, and finally establish affine transformation conversion equations from the control points. The transformation parameters for the entire field of view are solved using least squares, and the image is iteratively reprocessed according to the solved parameters until convergence is achieved. By registering high-resolution observation images with SDO/HMI full-disk continuum images, the fitting deviation is within 0.25 arcseconds.

Keywords: solar image registration; high-resolution images; full-disk solar images

1. Data Sources

The full-disk images used in our experiments 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 1-meter New Vacuum Solar Telescope (NVST) and the New Solar Telescope (NST). The SDO/HMI instrument has a spatial resolution of approximately 0.5043 arcseconds per pixel with image dimensions of 4096×4096 pixels. The NVST and NST images have pixel scales of 0.04 and 0.03 arcseconds per pixel, respectively.

[Figure 1: see original paper] shows the observational data. Figure 1(a) displays NVST TiO data observed on July 15, 2013 at 07:29:09 UT, with an effective region size of 2304×1920 pixels. Figure 1(b) shows the SDO/HMI continuum observation from July 15, 2013 at 07:29:15 UT, where the red box marks the approximate location of the NVST field of view within the SDO/HMI image. This image pair is used to illustrate the algorithm workflow.

2.1 Registration Method Workflow

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

1. Perform preliminary estimation of the NVST image' s orientation, scale, and position to obtain Rotation, Scaling, and Translation (RST) parameters.
2. Based on the RST parameters, rotate the SDO/HMI full-disk image and extract a sub-image with the same field of view as the NVST image.

3. According to the RST parameters and SDO/HMI' s pixel scale, downsample the NVST image to match SDO/HMI' s scale.
4. Apply Gaussian smoothing to the downsampled NVST image to reduce frequency aliasing during sampling. The smoothed, downsampled image is denoted as I_S.
5. Divide image I_S into N equally spaced, overlapping sub-blocks, each denoted as I_{S_i}.
6. For each sub-block I_{S_i} and the SDO/HMI sub-image I_R, use normalized cross-correlation to find the corresponding region.
7. For each pair I_{S_i} and I_{R_i}, measure their sub-pixel offset and designate the sub-block center as a corresponding control point.
8. Screen each control point pair, eliminating those with distances greater than a certain pixel threshold.
9. Establish affine transformation equations from the remaining control points and solve for RST parameters using least squares.
10. Calculate residuals and iteration count; if either convergence criteria are met, stop iteration; otherwise, return to step 2 and reprocess SDO/HMI and NVST images using the RST parameters from step 9.
11. Obtain the final converged RST parameters and perform registration.

Steps 6 through 9 constitute the core of the algorithm and are described in greater detail below. Note that after iteration begins, the RST parameters in steps 2-3 are updated for each subsequent iteration based on the previous results, meaning the algorithm reapplies smoothing to the images.

2.2 Determining Feature Control Points via Sub-blocking

Let I_S be the image to be registered and I_R the reference image. Divide I_S into N feature regions, denoted as the set $\{I_{S_i}|i=1,2,...,N\}$, where each region has dimensions $u \times v$. The normalized cross-correlation function between reference image I_R and image I_S is:

$$\mathrm{Corr}(x,y)=\frac{\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[I_R(s,t)-\bar{I}_R\right]\left[I_S(x+s,y+t)-\bar{I}_S\right]}{\sqrt{\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[I_R(s,t)-\bar{I}_R\right]^2\sum_{s=0}^{u-1}\sum_{t=0}^{v-1}\left[I_S(x+s,y+t)-\bar{I}_S\right]^2}}$$

where (x,y) are coordinates in I_S, $\bar{I}_R$ and $\bar{I}_S$ are the mean values of the regions covered by I_R and I_S, and the summations are over the overlapping areas.

Applying normalized cross-correlation to each I_{S_i} and I_R yields a correlation surface whose peak coordinate represents the integer-pixel matching position of the image center in I_R. From I_R, we can extract a feature region of the same size as I_{S_i} based on this position, obtaining each corresponding I_{R_i}. The collection of these is denoted as $\{I_{R_i}|i=1,2,...,N\}$.

For each pair of corresponding feature regions I_{S_i} and I_{R_i}, we calculate their standard cross-correlation function. Assuming the peak region of the cross-correlation distribution is obtained, we compute the centroid coordinates (m, n) using the modified moment method:

$$m = \frac{\sum_{b \in D} b \cdot I(b)}{\sum_{b \in D} I(b)}, \quad n = \frac{\sum_{b \in D} b \cdot I(b)}{\sum_{b \in D} I(b)}$$

where D represents the local area around the peak and $I(b)$ is the surface intensity value. These local centroid coordinates represent the sub-pixel offset between each pair of feature regions.

Based on these sub-pixel offsets, we establish coordinate correspondences for the center points of each image pair, obtaining N coordinate transformation control points between I_S and I_R. The relationship between control point pairs is described by set $P = \{(p_i^R, p_i^S) | i = 1, 2, ..., N\}$.

2.3 Least Squares Solution for Transformation Parameters

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

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

In matrix form, the error equation is:

$$V = B \cdot X - L$$

where $B = \begin{bmatrix} 1 & 0 & x_A & -y_A \\ 0 & 1 & y_A & x_A \end{bmatrix}$, $X = \begin{bmatrix} \Delta x & \Delta y & a & b \end{bmatrix}^T$, $L = \begin{bmatrix} x_B - x_A \\ y_B - y_A \end{bmatrix}$, with $a = (1+m)\cos\theta - 1$ and $b = (1+m)\sin\theta$. Here, (x_A, y_A) are pre-transformation coordinates, (x_B, y_B) are post-transformation coordinates, $(\Delta x, \Delta y)$ are translation parameters, m is the scale parameter, and θ is the rotation parameter.

Theoretically, only two control point pairs are needed to solve for the four transformation parameters. With three or more points, least squares can be used to solve for the RST parameters, which are then applied to transform the image to be registered into the reference image coordinate system.

Note that during planar coordinate transformation, mismatched point pairs must be screened by calculating inter-control-point distances. In practice, if the distance between control points exceeds 5 pixels (equivalent to 2.5 arcseconds), the pair is considered mismatched and eliminated. The RST parameters solved from the screened control points are used to iteratively process the SDO/HMI and NVST images until convergence.

3. Experimental Results and Analysis

In our experiments, sub-block size was set to 30 × 30 pixels with a block interval of 5 pixels. [Figure 3: see original paper] shows the overlapped region comparison after registering the NVST high-resolution image with the SDO/HMI full-disk image. The figure demonstrates that after registration, corresponding regions match perfectly except for differences in clarity.

To better observe the registration effect, we magnified the boundary region after overlaying the registered images, as shown in [Figure 4: see original paper]. The boundary details exhibit excellent matching, with pores, granules, and intergranular lanes connecting seamlessly.

Based on the registration results and SDO/HMI standard parameters, presents the derived P-angle and pixel scale for this NVST image, along with the field center position in the SDO/HMI full-disk image. The table shows an average residual of 0.31 SDO/HMI pixels, corresponding to approximately 0.15 arcseconds deviation.

[Figure 5: see original paper] displays the spatial distribution of these residuals. The residual distribution is not completely random, indicating distortion in the NVST image. This arises because some low-frequency atmospheric turbulence residuals remain even after image reconstruction in ground-based high-resolution observations, limiting the final fitting precision. Additionally, the 6-second time difference between the two image observations means some solar features had already evolved.

Multiple NVST and NST high-resolution images were matched with SDO/HMI full-disk images, with results summarized in . The maximum matching residual is approximately 0.5 pixels, equivalent to 0.25 arcseconds.

Experimental results show that different parameter selections affect the algorithm' s performance. [Figure 6: see original paper] illustrates the impact of initial parameter estimates on iteration count, with different symbols representing initial angle estimates of 30°, 35°, 40°, and 45°. As initial error increases, more iterations are required for convergence. When the initial angle error reaches approximately 30° (initial estimate of 45°), iteration count increases from 6 to 42.

[Figure 7: see original paper] demonstrates how control point filtering distance affects convergence speed. With large initial errors, higher thresholds (10 pixels) converge faster, while lower thresholds (5 pixels) perform better with small errors. At ~30° angle error, the iteration difference between thresholds is 28 iterations (favoring higher threshold), but only 9 iterations at ~10° error (favoring lower threshold).

[Figure 8: see original paper] shows the effect of different smoothing parameters on iteration count. Larger smoothing parameters increase iteration count and slightly reduce fitting quality. A smoothing parameter of 0.5 yields optimal convergence speed and results.

This paper proposes a field-matching algorithm for solar high-resolution and full-disk images, solving the registration problem for solar observations with different spatial resolutions and rotation angles. The method combines regional correlation matching with control point least-squares solving. Experiments with NVST and NST TiO images matched to SDO/HMI full-disk images demonstrate fitting deviations better than 0.25 arcseconds, enabling precise measurement of high-resolution image P-angles and pixel scales.

The method requires significant computational time for numerous small-region correlations and iterative calculations. Parameter selection also impacts iteration count. Small sub-block sizes increase matching points and computation while reducing fitting precision, whereas large sizes improve precision but reduce matching regions and affect overall registration quality. Block spacing primarily affects computational speed. Based on our experiments, a sub-block size of 30 pixels with 5-pixel spacing provides reasonable algorithm stability, though parameters can be adjusted for specific applications.

Furthermore, high-precision matching of high-resolution TiO images with SDO/HMI full-disk continuum images enables registration with any standard full-disk images, including SDO/HMI magnetograms, SDO/AIA multi-band observations, and even chromospheric full-disk images. This allows study of small-scale structures across different wavelengths and magnetic field configurations with 0.25 arcsecond accuracy.

This approach can be applied to any solar image registration with similar structural characteristics, such as TiO and G-band, H narrowband, or 10830 Å images, as well as H line-center images with GONG full-disk images, offering broad application prospects.

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