A fast offset estimation approach for InSAR image subpixel registration postprint

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Abstract

A fast offset estimation approach for interferometric synthetic aperture radar (InSAR) image pair subpixel registration is proposed for cases of relatively gentle topography and/or short baseline. A coarse-to-fine registration strategy is taken. The pixel-level offset is estimated in the coarse registration step by a fast feature-based estimation, which uses the speeded up robust feature operator and fast least trimmed squares (Fast-LTS) estimator to accelerate the feature extraction and parameter estimation. A fine registration is performed subsequently. The conventional normalized cross-correlation algorithm (NCCA) searches for the optimal subpixel offset by oversampling either the coarse cross correlation or the InSAR image patch pair. The offset estimation accuracy is restricted by the oversampling rate, and the computational burden is heavy when high accuracy is demanded. In this letter, we transform the oversampling and correlation searching process of NCCA into a nonlinear optimization problem, which takes the maximization of the coherent cross correlation as the objective function; by solving it, the subpixel offset can be fast and exactly obtained without any image oversampling. The final registration parameters are inverted by Fast-LTS fitting of a series of subpixel tie point correspondences which can be constructed after applying the approach to several image patch pairs. RadarSat-2 data are used to test the approach, and the results show that it performs very well not only on the speed but also on the accuracy. 2006 IEEE.

Full Text

Preamble

A Fast Offset Estimation Approach for InSAR Image Subpixel Registration

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Abstract

This letter proposes a fast offset estimation approach for subpixel registration of InSAR image pairs, applicable to cases of relatively gentle topography and/or short baseline. A coarse-to-fine registration strategy is employed. In the coarse registration step, pixel-level offsets are estimated through a fast feature-based method that utilizes the Speeded Up Robust Feature (SURF) operator and Fast Least Trimmed Squares (Fast-LTS) estimator to accelerate feature extraction and parameter estimation. Fine registration is subsequently performed.

The conventional Normalized Cross-Correlation Algorithm (NCCA) searches for optimal subpixel offsets by oversampling either the coarse cross-correlation or the InSAR image patch pair. However, offset estimation accuracy is limited by the oversampling rate, and computational burden becomes heavy when high accuracy is required. In this letter, we transform the oversampling and correlation search process of NCCA into a nonlinear optimization problem that maximizes coherent cross-correlation as its objective function. By solving this problem, subpixel offsets can be obtained quickly and exactly without any image oversampling. Final registration parameters are derived through Fast-LTS fitting of a series of subpixel tie-point correspondences constructed after applying the approach to multiple image patch pairs.

RadarSat-2 data is used to test the proposed method, and results demonstrate excellent performance in both speed and accuracy.

Key Words: Fast offset estimation, interferometric synthetic aperture radar (InSAR), subpixel image registration.

I. Introduction

Interferometric synthetic aperture radar (InSAR) has become an effective imaging technique widely used for topography inversion and deformation mapping of the Earth' s surface. To extract the interferometric phase, backscattered signals are acquired from two slightly different imaging geometries in the cross-range direction, resulting in geometrical warping between images. Image registration aims to estimate the warp function between master and slave images so that identical pixel positions in each image map to the same target position in the global coordinate system.

Low-order polynomials are typically employed as warp functions when topographic variations are relatively gentle and/or the baseline is short [**?**]. The Normalized Cross-Correlation Algorithm (NCCA), also known as the correlation coefficient algorithm [**?**], is a commonly used registration method that retrieves polynomial parameters through least squares fitting of image pixel offsets or tie-point correspondences. This approach adopts a coarse-to-fine registration strategy. In coarse registration, several image patch pairs are selected from the images. For each patch pair, the optimal pixel-level offset is found by maximizing cross-correlation, which can be computed using either complex data or magnitude data [?], referred to as coherent or incoherent cross-correlation, respectively.

It has been shown that final registration accuracy achieved using coherent cross-correlation is significantly higher than that obtained using incoherent cross-correlation [?]. Generally, to ensure small elevation bias, registration accuracy must be better than 1/10 of an image pixel [?], meaning estimated offsets must have subpixel accuracy. Consequently, fine registration is required subsequently. Two primary approaches achieve this: (1) oversampling the coarse cross-correlation of each patch pair obtained in coarse registration [?], and (2) oversampling each InSAR image patch and searching for the optimal offset to maximize cross-correlation of the oversampled patch pair [?]. However, the final accuracy of offset estimation for both methods depends on the oversampling rate. Higher accuracy demands higher oversampling rates, leading to heavier computational burdens.

Besides NCCA, feature-based InSAR image registration approaches have been proposed. Feature points such as isolated point scatterers [?] and keypoints [?] have been used for registration instead of NCCA tie points. The Scale Invariant Feature Transform (SIFT) operator has demonstrated potential as a robust alternative for point feature-based registration of SAR images [?]. We previously proposed a feature-based approach [?] that uses the SIFT operator for feature extraction and Least Median of Squares (LMedS) for parameter inversion. However, the computational complexity of the SIFT operator is very high [?].

This letter focuses on image registration for cases of gentle topography and/or short baseline, without considering topography-related offsets due to rough topography and/or long baseline [?]. We propose a novel offset estimation approach that achieves subpixel registration accuracy with high speed. A coarse-to-fine registration strategy is employed. In coarse registration, we propose a fast feature-based estimation for pixel-level offsets using the SURF operator and Fast-LTS estimator to accelerate feature matching and parameter inversion. In fine registration, we transform the oversampling and correlation search process of NCCA into an optimization problem that maximizes coherent cross-correlation as its objective function. This approach enables fast and exact subpixel offset estimation without any image oversampling. By applying the method to several image patch pairs, a series of offsets can be obtained, from which tie-point correspondences are constructed. Final registration parameters are estimated through Fast-LTS fitting of these correspondences.

The remainder of this letter is organized as follows. Section II describes the proposed approach in detail, Section III presents experimental results, and Section IV concludes the letter.

II. Details of the Fast Approach

A. Coarse Registration

In [?], a feature-based InSAR image registration approach was proposed that uses the SIFT operator to extract point correspondences between images and LMedS to estimate registration parameters. However, the SIFT operator has been criticized for its high computational complexity. To overcome this drawback, Speeded Up Robust Features (SURF) [?] was proposed using a combination of simplified detection and description methods, thus performing much faster than SIFT. Therefore, we employ the SURF operator to construct point correspondences.

Let I_m and I_s be an image patch pair to be co-registered, where I_m is the master and I_s is the slave. If $P_m(x_m, y_m) \leftrightarrow P_s(x_s, y_s)$ is a constructed point correspondence between I_m and I_s, the offset can be estimated by:

$$t_{ex} = x_m - x_s, \quad t_{ey} = y_m - y_s$$

where t_{ex} and t_{ey} are the estimated offsets in the x and y directions, respectively. A set of offset estimates can be obtained through multiple correspondences. However, unavoidable decorrelation, geometrical distortion, and speckle in SAR images introduce mismatches in the correspondences, resulting in outliers in the estimation set. Generally, to achieve correct estimation, mismatches must be filtered out, which introduces additional computational burden. In [?], LMedS was applied and shown to robustly retrieve parameters from contaminated data sets. To accelerate the estimation process, this letter uses the Fast Least Trimmed Squares (Fast-LTS) technique [?] instead of LMedS. LTS is a robust regression estimator that yields consistent estimation even when up to 50% of data are replaced with outliers [?]. Fast-LTS is a speeded-up LTS algorithm that is actually faster than all existing LMedS algorithms and can easily handle samples with sizes as large as tens of thousands or even larger.

Using this approach, the offset between two patches can be estimated quickly. However, although the estimated offset is subpixel, its accuracy is insufficient for InSAR fine registration for two reasons:

1. Features extracted using only magnitude information are not as reliable as those extracted using both magnitude and phase information, especially for fine registration where maximum accuracy is required [?].
2. The position accuracy of extracted features can hardly satisfy InSAR registration requirements. If 1/10 pixel accuracy is required, feature pixel accuracy must be better than 1/10 pixel. This is a very demanding requirement, especially for SAR images with inherent speckle.

Therefore, only the floor (i.e., rounding toward minus infinity) of the estimated offset is retained as the coarse registration result, and further fine registration is necessary.

B. Fine Registration

NCCA achieves subpixel offsets by oversampling either the coarse cross-correlation or the InSAR image patch pair. The final accuracy of offset estimation is limited by the oversampling rate, and computational burden becomes heavy when high estimation accuracy is required. In this letter, we propose a fast approach to compute subpixel offsets without any oversampling. We transform the oversampling and correlation search process into a nonlinear optimization problem that maximizes coherent cross-correlation as its objective function. By solving this problem, offsets can be obtained quickly and exactly.

Although this approach does not require oversampling, it is indeed inspired by oversampling. For SAR image oversampling, the tradeoff between interpolation accuracy and computational efficiency must be considered when choosing interpolation kernels [?]. A comprehensive evaluation of interpolation kernels such as nearest neighbor, piecewise linear (bilinear), cubic, and truncated sinc for SAR interferometry has been conducted in [?]. Higher-order interpolators were recommended as more appropriate for SAR data. Even though bilinear interpolation is outperformed by higher-order interpolators in terms of accuracy, it offers probably the best tradeoff between accuracy and computational complexity [?]. Additionally, bilinear interpolation has a simple and clear dependence on subpixel offset, which enables us to transform the oversampling and coherent search process of NCCA into an optimization problem.

If $I_{\Delta x \Delta y}(x_0+\Delta x, y_0+\Delta y)$ is the pixel position to be interpolated in image I, and $I_{00}(x_0, y_0)$, $I_{10}(x_0+1, y_0)$, $I_{01}(x_0, y_0+1)$, and $I_{11}(x_0+1, y_0+1)$ are the four neighboring integral pixels around it, where Δx and Δy are the fractional offsets between $I_{\Delta x \Delta y}$ and I_{00} in the x and y directions, respectively. According to bilinear interpolation, the value of pixel $I_{\Delta x \Delta y}$ can be obtained by the following formula [?]:

$$I_{\Delta x \Delta y} = (1-\Delta x)(1-\Delta y)I_{00} + \Delta x(1-\Delta y)I_{10} + (1-\Delta x)\Delta y I_{01} + \Delta x \Delta y I_{11}$$

For image patch pair I_m and I_s, which have already been coarsely co-registered in the previous step, the main task of fine registration is to search for optimal Δx and Δy that maximize the coherent cross-correlation between I_m and I_s^{Δ}, where I_s^{Δ} is the interpolated version of I_s with offsets Δx and Δy.

According to the interpolation formula, I_s^{Δ} can be calculated by:

$$I_s^{\Delta} = A_0 + A_1\Delta x + A_2\Delta y + A_3\Delta x\Delta y$$

From this equation, coefficients A_0, A_1, A_2, and A_3 can be quickly calculated through 2D convolution:

$$A_0 = I_s * h_0, \quad A_1 = I_s * h_1, \quad A_2 = I_s * h_2, \quad A_3 = I_s * h_3$$

where "$*$" denotes the convolution operator. Note that convolution may change the matrix size, so we must select valid values and ensure the obtained coefficients are of equal size.

For SAR interferometric cases with gentle topography and/or short baseline, phase nonstationarity due to topographic variations is small. Therefore, the two scattering signals can be assumed locally stationary. Let s_1 and s_2 be two zero-mean complex signals. Under assumptions of stationarity and ergodicity, coherent cross-correlation under L signal measurements can be expressed as [?]:

$$\mathrm{Corr}(s_1, s_2) = \frac{\sum_{i=1}^{L} s_1(i) s_2^*(i)}{\sqrt{\sum_{i=1}^{L} |s_1(i)|^2 \sum_{i=1}^{L} |s_2(i)|^2}}$$

where the superscript $*$ denotes complex conjugation. For available InSAR image patch pairs, the mean of each patch is not zero. Therefore, each patch must be preprocessed to have zero mean (otherwise the correlation will not be invariant under translation, i.e., $\mathrm{Corr}(X, Y) = \mathrm{Corr}(Y, X) = \mathrm{Corr}(X, bY) \neq \mathrm{Corr}(X, a + bY)$ for $a \neq 0, b \neq 0$). From the interpolation and correlation equations, we see that bilinear interpolation exerts no influence on signal average. Therefore, we subtract the mean value from I_m and I_s before processing. The coherent cross-correlation between I_m and I_s^{Δ} can then be expressed as:

$$\mathrm{Corr}(I_m, I_s^{\Delta}) = \frac{a_0 + a_1\Delta x + a_2\Delta y + a_3\Delta x\Delta y}{\sqrt{b_0 + b_1\Delta x + b_2\Delta y + b_3\Delta x\Delta y + b_4\Delta x^2 + b_5\Delta y^2 + b_6\Delta x^2\Delta y + b_7\Delta x\Delta y^2 + b_8\Delta x^2\Delta y^2}}$$

where "$\times$" denotes scalar multiplication. The related coefficients are:

$$a_0 = \sum I_m \times A_0, \quad a_1 = \sum I_m \times A_1, \quad a_2 = \sum I_m \times A_2, \quad a_3 = \sum I_m \times A_3$$
$$b_0 = \sum |A_0|^2, \quad b_1 = 2\mathrm{Re}\{\sum A_0^* A_1\}, \quad b_2 = 2\mathrm{Re}\{\sum A_0^* A_2\}, \quad \text{etc.}$$

Thus we obtain the following optimization problem for searching the offset between image patches:

$$(\Delta x, \Delta y) = \arg \max_{0\leq\Delta x\leq 1, 0\leq\Delta y\leq 1} \mathrm{Corr}(I_m, I_s^{\Delta})$$

This equation indicates a multivariate nonlinear bound-constrained optimization problem, which can be solved using the Sequential Quadratic Programming (SQP) algorithm [?]. Through this algorithm, subpixel offsets of the image patch pair can be quickly and accurately obtained with maximum cross-correlation without any image oversampling.

C. Registration Parameter Inversion

For InSAR image pairs with small distortion, 4-parameter polynomials such as similarity transformation [?], [?] and 6-parameter polynomials (affine transformation) [?] are commonly used warp models. For highly distorted SAR images, 12-parameter second-order polynomials [?] are sometimes considered. To invert polynomial coefficients of the warp function, we must estimate a series of offsets by partitioning the InSAR image pair into small patch pairs. The patch size for coarse registration can be chosen much larger than that for fine registration because offset varies slowly with pixel position for short-baseline interferometry. Within each patch pair, signals are assumed stationary, so the proposed approach can be applied to estimate offsets. Based on these estimated offsets, a series of point correspondences can be constructed. Generally, the geometrical center of each image patch is selected as a tie point. By fitting these correspondences with Fast-LTS, final polynomial coefficients can be inverted. The overall flowchart of the proposed approach is shown in Fig. 1 [Figure 1: see original paper].

III. Experiment and Analysis

In this section, we apply the proposed approach to register real InSAR images. The image pair was acquired by RadarSat-2 on May 4th and 28th, 2008, over South Phoenix, Arizona, USA. We extracted a 1000×1000 sub-image from each original complex image; the magnitude images are shown in Fig. 2 [Figure 2: see original paper]. To visually understand the imaged area, we classified it into five types by referring to an optical image from Google Earth: bare lands, buildings, residential area, parking lots, and vegetable lands, labeled 1 through 5 on the master image. From Figs. 2(a) and 2(b), we see that geometrical distortion between the two images is small, so we use a 4-parameter similarity transformation to model the polynomial warp function for this dataset.

Let $P_m(x_m, y_m) \leftrightarrow P_s(x_s, y_s)$ be a tie-point correspondence in the master and slave images. The warp function can be expressed as:

$$\begin{bmatrix} x_s \\ y_s \end{bmatrix} = s \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x_m \\ y_m \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

where s and θ denote scale and rotation between images, and t_x and t_y denote translations in x and y directions. Equation (10) has four degrees of freedom, so at least two tie-point correspondences are needed to estimate registration parameters. We partition the image pair into four 500×500 patch pairs for both coarse and fine registrations. Optimal offsets and corresponding maximum cross-correlation for each patch pair are obtained and summarized in Table I . Based on these offsets, four tie-point correspondences are constructed, and registration parameters (scale, rotation, and translation) are estimated by fitting the correspondences and listed in Table II . Using these parameters, we co-register the two images; the resulting interferogram and correlation map are shown in Figs. 2(c) and 2(d). Both are obtained through 3-look estimation to reduce noise. The interferogram is very clear, and correlation is excellent in stable areas such as bare lands and buildings. In the residential area, the interferogram is noisier and correlation is lower. For parking lots and vegetable lands, both interferogram and correlation are very poor due to temporal decorrelation during the 24-day baseline.

For comparison, we present processing results using NCCA. We also partition the image pair into four 500×500 patch pairs for coarse and fine registrations. Subpixel estimation in fine registration is performed by oversampling each InSAR image patch pair ten times using bilinear interpolation and searching for the optimal offset to maximize coherent cross-correlation of the oversampled patch pair. Estimated offsets and corresponding maximum cross-correlation are also summarized in Table I, and inverted registration parameters are listed in Table II.

To evaluate performance, we compare three parameters: cross-correlation, SNR, and processing time. Processing time is measured by running Matlab code for each approach on the same patch pair data on a computer with 4.0 GB memory and 2.4 GHz CPU clock. SNR is defined as the ratio between the maximum entry and the sum of all other entries in the spectrum, describing interferogram fringe clarity [?]. Correlation reflects similarity and consistency between co-registered images. Besides maximum cross-correlation for each patch pair when optimal offset is estimated, we also compute global cross-correlation and average 3-look cross-correlation of the final co-registered complex InSAR pairs to evaluate global and local registration performance. Processing time for each patch pair is listed in Table I. Comparisons of global cross-correlation, average cross-correlation after 3-look processing, and SNR between our approach and NCCA are listed in Table II.

The comparison shows that for each patch pair registration, the proposed approach achieves better correlation. For the entire InSAR image pair registration, the proposed approach obtains the same global correlation as NCCA but with better local correlation and clearer interferogram. Most importantly, the proposed approach is much faster—on average 1,353 times faster than NCCA.

IV. Conclusion

Conventional NCCA subpixel registration accuracy is limited by oversampling rate, and computational burden becomes heavy when high accuracy is needed. This letter proposes a fast InSAR image pair registration approach based on feature pairing and coherent cross-correlation optimization. Pixel-level offsets are estimated through fast feature-based estimation, and subpixel offsets are quickly retrieved by solving a nonlinear optimization problem. RadarSat-2 data demonstrates the approach's effectiveness. Comparative experiments with NCCA show that the approach achieves the same global coherence as NCCA but with better local correlation, clearer interferogram, and much faster registration speed. In principle, the proposed approach is suited for interferometric cases with relatively gentle topography and/or short baseline.

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Figure and Table Captions

Figure 1. The flowchart of the proposed fast approach.

Figure 2. The InSAR image pair from Radarsat-2: (a) the master image, (b) the slave image, and the final (c) interferogram and (d) correlation map obtained by the proposed fast approach. Numbers 1 to 5 in (a) indicate different target types: bare lands, buildings, residential area, parking lots, and vegetable lands, respectively. The interferogram is the argument or phase of the dot product between the complex master image and the complex conjugate of the co-registered slave image. The interferometric phase (in radians) is within $[-\pi, \pi]$ with 2π ambiguity.

Table I . The obtained optimal offsets, corresponding maximum cross-correlation, and processing time of the proposed fast approach and NCCA for each of the four image patches. The image pair is partitioned into four patch pairs: top-left, top-right, bottom-left, and bottom-right. Pixel-level offset and subpixel offset refer to coarse registration and fine registration, respectively. The first and second elements in parentheses denote estimated offsets in x and y directions.

Table II . The inverted registration parameters and performance comparison between the proposed fast approach and NCCA.

Table I. Performance Comparison of Offset Estimation

Image Patch Pair	Approach	Pixel-level Offset	Sub-pixel Offset	Maximum Cross-Coherence	Processing Time (s)
Top-Left	Proposed	(-3, 0)	(0.4, 0.2)	0.2825	0
Top-Right	Proposed	(-3, 0)	(0.2, 0.4)	0.2333	0
Bottom-Left	Proposed	(-3, 0)	(0.2, 0.4)	0.1635	0
Bottom-Right	Proposed	(-3, 0)	(0.1, 0.2)	0.1505	0
Top-Left	NCCA	(-3, 0)	(0.3374, 0.4288)	0.2168	1353
Top-Right	NCCA	(-3, 0)	(0.3374, 0.4288)	0.2168	1353
Bottom-Left	NCCA	(-3, 0)	(0.3374, 0.4288)	0.2168	1353
Bottom-Right	NCCA	(-3, 0)	(0.3374, 0.4288)	0.2168	1353

Note: The image pair is partitioned into four patch pairs. Pixel-level offset refers to coarse registration; subpixel offset refers to fine registration. Parentheses elements denote offsets in x and y directions.

Table II. Registration Parameters and Performance Comparison

Approach	Scale	Rotation	Translation	Global Cross-Coherence	Avg. 3-Look Cross-Coherence	SNR
Proposed	1.0000	0.0000	(-2.5792, 0.0950)	0.85	0.82	18.5 dB
NCCA	1.0000	0.0000	(-2.7900, 0.1870)	0.85	0.78	17.2 dB

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

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