The appropriate parameter retrieval algorithm for feature-based SAR image registration (Postprint)

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Abstract

This paper is dedicated to investigate the appropriate parameter retrieval algorithm for feature-based synthetic aperture radar (SAR) image registration. The widely-used random sample consensus (RANSAC) is observed to be instable for its inappropriate estimation strategy and loss function for SAR images. In order to enable a stable and robust registration for SAR, an extended fast least trimmed squares (EF-LTS) is proposed which conducts the registration by least squares fitting at least half of the correspondences to minimize the squared polynomial residuals instead of fitting the minimal sampling set to maximize the cardinality of the consensus set as RANSAC. Experiment on interferometric SAR image pair demonstrates that the proposed algorithm behaves very stably and the obtained registration is averagely better than that by RANSAC in terms of cross-correlation and spectral SNR. By this algorithm, a stable estimation for any kind of 2D polynomial warp model with high robustness and accuracy can be efficiently achieved. Thus EF-LTS is more appropriate for SAR image registration. 2012 SPIE.

Full Text

Preamble

The Appropriate Parameter Retrieval Algorithm for Feature-Based SAR Image Registration

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ABSTRACT

This paper investigates the appropriate parameter retrieval algorithm for feature-based synthetic aperture radar (SAR) image registration. The widely-used random sample consensus (RANSAC) is observed to be unstable for SAR images due to its inappropriate estimation strategy and loss function. To enable stable and robust registration for SAR, we propose an extended fast least trimmed squares (EF-LTS) that conducts registration by least-squares fitting at least half of the correspondences to minimize squared polynomial residuals, rather than fitting a minimal sampling set to maximize consensus set cardinality as RANSAC does. Experiments on interferometric SAR image pairs demonstrate that the proposed algorithm behaves very stably and achieves, on average, better registration than RANSAC in terms of cross-correlation and spectral SNR. This algorithm can efficiently achieve stable estimation for any kind of 2D polynomial warp model with high robustness and accuracy. Thus, EF-LTS is more appropriate for SAR image registration.

Keywords: Extended fast least trimmed squares (EF-LTS), feature-based image registration, parameter estimation, random sample consensus (RANSAC), synthetic aperture radar (SAR).

1. INTRODUCTION

Synthetic aperture radar (SAR) is an irreplaceable remote sensing technique that has long been used in Earth observation and environmental monitoring due to its unique advantages such as independence from weather and sunlight conditions. The amount of available SAR data has increased dramatically with the launch and operation of numerous spaceborne and airborne SAR systems, making it possible to jointly process multiple images for accurate scene understanding and target perception. Since SAR images may be acquired from different imaging geometries and/or by different sensors, there is always geometrical warping between images that must be aligned before further application. The task of image registration is to estimate the warp function between images so that the same pixel position in each image maps to the same target position in the global coordinate system.

Numerous SAR image registration algorithms have been proposed to date. This paper focuses exclusively on feature-based registration approaches, which perform registration by first extracting features from images. Contour, region, line, and point features are commonly used for SAR image registration. The first three features and their combinations (i.e., multi-features) are typically employed for registering images from different modalities, such as SAR and optical cameras. For registering SAR images with inherent speckle and distortion, point features are much clearer and easier to extract. We have conducted a comprehensive evaluation of commonly-used point features for SAR image registration —including tie points, Harris corners, SIFT, and SURF—in terms of geometrical invariance of features, extraction speed, localization accuracy, geometrical invariance of descriptors, matching speed, robustness to decorrelation, and flexibility to image speckling. SURF has been shown to be more appropriate and competent for general SAR image registration [?].

For feature-based registration approaches, an important procedure after feature extraction is to retrieve the warp function—that is, to estimate the registration parameters from the constructed feature correspondences. However, for general SAR images, there are always unavoidable mismatches in the correspondences since the two SAR images are acquired either spatially or temporally separately, not to mention the influences from unavoidable system noise, environmental interference, and the non-robustness of feature descriptors and matching algorithms. All these factors cause mismatches in the correspondences and lead to potential errors in warp estimation. Usually, it is difficult to obtain a priori information to exclude these mismatches beforehand. Therefore, to accurately retrieve parameters from these error-prone correspondences, robust outlier-insensitive algorithms are essential.

Additionally, SAR image warp estimation presents another difficulty compared to optical image registration. SAR acquires target scattering along a slant range, which cannot be modeled as a central projection like the pinhole imaging of optical cameras. Consequently, the warp model between SAR images depends on system parameters, imaging geometry, and target relief. Theoretically, we cannot use global epipolar geometry or homography to model the geometrical warping as we can for optical images. For convenient coregistration, when system parameters and imaging geometry are fixed, we can conventionally approximate the warp function as a low-order polynomial if the images are acquired over gently topographic areas with relatively short baselines [?]. This means we focus on global registration while neglecting local discrepancies. This strategy should also be adopted when retrieving registration parameters. In existing literature on feature-based SAR image registration, random sample consensus (RANSAC) [?] has been widely used and recommended for warp estimation [?]. RANSAC performs estimation by randomly sampling a minimal sampling set (MSS) to achieve a warping estimation, then checks the entire dataset to find correspondences consistent with this estimation to construct a consensus set (CS). These two steps are repeated iteratively until the probability of finding a larger CS drops below a certain threshold [?]. Besides RANSAC, least median squares (LMedS) [?] and fast least trimmed squares (Fast-LTS) [?] have also been used [?]. Many other registration approaches exist, which can be found in related review articles [?].

Although many feature-based registration methods for SAR images have been proposed, many approaches appear to be introduced from the optical image registration domain. This poses several open problems that have not been perfectly solved. This paper investigates the appropriate parameter retrieval approach for SAR image registration. We find that commonly-used RANSAC is unstable in parameter estimation based on a registration experiment on interferometric SAR (IFSAR) image pairs. This instability derives from its inappropriate loss function and inherent parameter retrieval mechanism. Therefore, we propose a new estimation algorithm based on the robust Fast-LTS scheme, which we name extended Fast-LTS (EF-LTS). Experiments on IFSAR image pairs demonstrate that EF-LTS is more stable and robust than RANSAC, making it more competent for SAR image registration.

The remainder of this paper is organized as follows. Section 2 first evaluates RANSAC for SAR image registration, then develops the robust EF-LTS for general SAR image registration in Section 3. Section 4 concludes the paper.

2. EVALUATION OF RANSAC FOR SAR IMAGE REGISTRATION

RANSAC has been widely used and recommended for parameter retrieval in many feature-based SAR image registration approaches [?]. Unlike least squares (LS), which uses all available data to estimate parameters, RANSAC conducts estimation using a few-to-many or local-to-global strategy. When RANSAC performs estimation, it first randomly samples a minimal sampling set (MSS) from the constructed correspondences to achieve a warp function estimation. The cardinality of the MSS is related to the degrees of freedom (DoF) of the warp function—that is, the minimum number needed to determine the warp parameters. For example, the cardinality is three for an affine transformation with six DOFs.

The entire dataset is then checked to find correspondences consistent with the estimated warping in order to construct a larger consensus set (CS). These two steps are repeated iteratively until the probability of finding a larger CS drops below a certain threshold [?]. The estimation with the largest CS cardinality is selected as the optimal parameter estimation. This local-to-global strategy is validated under the assumption that any MSS composed entirely of inliers will generate the "true" value of the parameter vector [?]. However, in real registration scenarios, this is difficult to achieve due to unavoidable noise and local image distortion. Therefore, it is hard to obtain an invariant parameter estimation based on each MSS configuration of inliers. This estimation uncertainty is more severe for SAR image registration because SAR image warping varies pixel by pixel, and the approximated low-order polynomial warping is based on a strategy that focuses on global registration while neglecting local discrepancies. The use of a local-to-global estimation strategy may magnify local distortion, which can further increase estimation uncertainty and degrade global registration accuracy even when the largest CS cardinality is achieved.

To demonstrate the estimation uncertainty of RANSAC, we designed an experiment to coregister a spaceborne IFSAR image pair, as shown in Figure 1 Figure 1: see original paper and (b). The two images were acquired by RadarSat-2 on May 4 and 28, 2008, respectively. The scene covers the South Phoenix, AZ area and features a region with vegetated lands and buildings. We first used SURF [?, ?] to construct feature correspondences from the images, then applied

RANSAC to retrieve the affine warp parameters. To evaluate RANSAC' s estimation stability, we executed RANSAC 100 times and, based on the parameters obtained from each execution, coregistered the original complex image pair to calculate the average three-look coherent cross-correlation (CC) and spectral SNR [?], which serve as evaluation criteria. CC evaluates the similarity and consistency of the coregistered IFSAR complex image pair. Spectral SNR, defined as the ratio between the maximum entry and the sum of other entries in the spectrum, describes the clarity of the interferogram fringe [?].

The obtained affine parameters (a, b, c, d, tx, and ty) and the two criteria (CC and SNR) for each execution are illustrated in Figure 2 [Figure 2: see original paper]. The mean and standard deviation of the parameters, CC, and SNR are listed in Table 1 . It is clear from Figure 2 and Table 1 that RANSAC cannot achieve stable registration because the obtained parameters vary with each algorithm execution. This estimation uncertainty impacts the potential accuracy and reliability of further applications such as DEM inversion. Besides this uncertainty, an interesting phenomenon can be observed: even with the same CS cardinality, the obtained parameters are still different.

Figure 3 [Figure 3: see original paper] exemplifies the parameters, CC, and SNR obtained from 48 executions with the same CS cardinality, from which one can observe that estimation uncertainty persists despite identical cardinality. This indicates that the extracted inliers composing the final CS are in fact still varied; otherwise, the parameters would be stable because they are retrieved by simply LS fitting the inliers.

The estimation uncertainty of RANSAC observed above indeed derives from its inappropriate retrieval strategy and loss function, making it unsuitable for SAR image registration. To achieve stable registration for SAR images, a conceivable improvement is to estimate parameters using more correspondences than just an MSS and employ an appropriate loss function. This yields better and more stable estimation because the sampled support will more accurately reflect the true support. This insight inspired our development of an alternative approach to robust parameter regression.

3. THE DEVELOPED EF-LTS FOR SAR IMAGE REGISTRATION

Classical least squares (LS) has long been a widely-used linear regression estimator due to its computational simplicity and mathematical elegance. However, this estimator is increasingly criticized for its dramatic lack of robustness. To address this problem, other robust regression approaches were proposed, such as LMedS [?] and least trimmed squares (LTS) [?]. LMedS performs regression by minimizing the median of squared residuals rather than the sum of squared residuals as in LS. This makes LMedS very robust in dealing with outliers because its breakdown point can be as high as 50%. LTS is a modified form of LS that can also robustly obtain a consistent estimation even when 50% of the dataset are outliers. Like LS and LMedS, LTS is designed to fit the linear model:

where Xi = [xi1, xi2, ···, xip] T is the explanatory variable, yi is the response variable, = [1, 2, ···, p] T is the unknown parameter to be estimated, ei is the error term, n is the sample size, and p denotes the dimension of Xi. The loss function of LTS is:

Q Minimize r y where e is the estimation of , (r2)i represents the ith element of the ordered squared residuals (r2)1 ···(r2)i ···(r2)n, and h is the trimming constant related to the number of inliers in the dataset. From (2) we see that LTS conducts estimation by LS fitting the h-subset to minimize squared residuals rather than fitting the MSS to maximize CS cardinality, making it more appropriate for parameter estimation than RANSAC. LTS also has several advantages over LMedS: its loss function is smoother and thus less sensitive to local effects, and its statistical efficiency is much better with a faster convergence rate [**?**]. However, LTS' s disadvantage is its high computational cost as dataset size increases. To accelerate it, Rousseeuw and Van Driessen [**?**] proposed a Fast-LTS algorithm that is actually faster than all existing LMedS algorithms and can handle sample sizes n as large as tens of thousands or even larger. Based on the principle that any approximation to the LTS regression coefficients can be used to compute another approximation yielding an even lower loss Q, a concentration step (C-step) was proposed in the fast algorithm:

Step 1. Calculate the parameters eold by LS fitting Hold.

Step 2. Compute the residuals rold based on the obtained eold. Sort the squared residuals ascendingly and obtain a permutation subjected to (rold 2) (1) ···(rold 2) (i) ···(rold 2) (n).

Step 3. Construct the new h-subset Hnew={ (1), (2), ···, (h)} and estimate the new parameters enew by LS fitting Hnew.

It has been proved that the Q value of parameters enew is not larger than that of parameters eold after executing a C-step, allowing us to obtain more accurate parameter estimation. In practice, Q converges after a few steps, thus guaranteeing efficient estimation. Based on the C-step, Fast-LTS conducts regression as follows [**?**]:

Step 1. Randomly draw a p-subset as the parameter set e0. Compute the n residuals r0 based on e0 and construct an initial h-subset H0={ (1), (2), ···, (h)} subjected to (r0 2) (1) ···(r0 2) (i) ···(r0 2) (n). Carry out two C-steps on H0. Repeat the above procedures 500 times.

Step 2. For the 10 results with the lowest Q, carry out C-steps until convergence. The solution e with the lowest Q is selected as the optimal estimation.

The trimming constant h is set between [(n+p+1)/2] and n, where [x] denotes the smallest integer larger than x. The breakdown value of the algorithm is (n-h+1)/n. A good compromise between breakdown value and statistical efficiency can be obtained by setting h=[0.75n] if the dataset contains less than 25%

contamination [?]. When n is larger, the algorithm employs a nested extension approach to enable efficient estimation.

From (1) we see that Fast-LTS is only appropriate for 1D linear regression. However, for SAR image registration, we need to fit a 2D polynomial regression:

where n is the number of constructed correspondences, N is the order of the polynomial, a and b are the polynomial coefficients, (xsi, ysi) and (xmi, ymi) denote the ith extracted correspondence in slave and master images respectively, and i and i are error terms assumed to be normally distributed with zero mean and unknown standard deviation. The polynomials in (3) can be transformed to the following linear regression problem:

mi mi where   and   are the unknown parameters to be estimated, p indicates the number of unknowns, and p=(N +1)(N + 2)/2.

Therefore, warp function estimation for SAR image registration can be transformed into the optimization problems:

Minimize Minimize 2)i represents the ith element of the ordered squared residuals (rx where (rx e and e are the estimations of   and , respectively. 2)1   ···(rx 2)i   ···(rx 2)n, and similarly for (ry We can see that each of the two optimization problems in (5) is of the standard form of (2). Therefore, a straightforward solution to (5) can be obtained by applying Fast-LTS separately to conduct the estimations, i.e., treating the 2D regression as two independent 1D regressions. This approach is feasible but may introduce redundancy resulting in unnecessary computational load because the feature positions in the two image directions are inherently tied to each other, meaning that for the ith feature, selecting xi also indicates selecting yi without extra computation. This signifies that we can effectively combine the two independent 1D regressions into a true 2D regression, which is the extended Fast-LTS (EF-LTS) we propose. It works as follows:

Step 1. Randomly draw p matches from the constructed correspondences to obtain initial parameters e0 and e0 by LS fitting, then calculate initial residuals r0x and r0y by:

Then construct the initial h-subsets Hx0 and Hy0 by:

Carry out two C-steps on Hx0 and Hy0 to further obtain h-subsets Hx2 and Hy2 with smaller values of Qx and Qy, respectively. Iteratively repeat the above procedures T times to obtain sets of h-subsets Hx2 and Hy2.

Step 2. Select the 10 Hx2 and Hy2 with the lowest values of Qx and Qy if T is larger than 10; otherwise, use all obtained Hx2 and Hy2. Carry out C-steps on these selected h-subsets until convergence. The solutions with the lowest values of Qx and Qy are selected as the raw estimations er and er.

Step 3. Calculate residuals rrx and rry based on the estimated er and er:

and estimate the error scales by:

where C1 and C2 are correction factors to achieve consistency at Gaussian error distributions [?]. Calculate the weights by:

Select credible correspondences in both x and y directions:

where "&" indicates the logical AND operator. The final estimations ef and ef are obtained by LS solving the following optimizations:

arg min arg min which in fact indicates weighted LS.

Step 3 is crucial because it enables the proposed EF-LTS to achieve more accurate and stable estimation than the original LTS. The obtained estimator still possesses a high breakdown point but is more statistically efficient and can yield all standard quantities such as t-values and confidence intervals. Operation (11) indicates that feature correspondences correctly matched in both image directions are selected as final inliers. This operation is necessary for accurate estimation because features are extracted and constructed without directional bias. Mismatching in one direction usually affects matching in the other direction, though a few exotic cases cannot be ruled out. The bound in (10) is selected as 2.5 because in a Gaussian situation, very few residuals exceed 2.5 .

In the original Fast-LTS, the number of random samplings is set to a constant 500. This is irrational because accurate estimation requires only that at least one p-match among all T random p-matches be "clean." Let q denote the percentage of inliers in the dataset; then the probability of having at least one "clean" p-match among all T random p-matches can be expressed as:

We know that the trimming constant h is chosen beforehand according to the inlier percentage, thus a good estimation of q can be obtained by:

Table 2 shows the sampling number T under given polynomial order N and inlier percentage q when =0.99.

Thus, if we specify a required false alarm rate for the estimation (i.e., specify), the sampling number T can be calculated by combining (13) and (14):

log 1 log 1

Equation (15) indicates that iteration in the proposed algorithm is related to the inlier percentage rather than the inlier number, enabling fast estimation even when the number of outliers is large. Table 2 lists the sampling number T under given N and q when =0.99, showing that for second-order polynomials, the worst-case sampling number of 293 is still smaller than 500, making the use of 500 samplings unnecessary and increasing computational load in this case. For third-order polynomials when q is smaller (meaning more outliers), however, constant sampling would be insufficient for accurate estimation.

When the correspondence number n is larger, a nested extension similar to the original Fast-LTS can also be employed. We randomly partition the correspondences into M subsets with nearly equal cardinality (such as 300), and the trimming constant hs and sampling number Ts for each subset are reduced by M times compared to their original counterparts h and T, i.e., hs=[h/M] and Ts=[T/M]. For each subset, we execute Step 1 to obtain Ts hs-subsets of Hx2 and Hy2. Based on all obtained T hs-subsets, we then execute the following two steps on all constructed correspondences with the original h and T. This approach still achieves fast and robust estimation.

To evaluate EF-LTS performance for SAR image registration, we applied it to register the IFSAR image pair shown in Figure 1 (a) and (b). Similarly, feature correspondences were first constructed using SURF, then EF-LTS was run 100 times to retrieve affine parameters and calculate CC and SNR. The estimated parameters and CC and SNR values varying with each execution are shown in Figure 2. The mean and standard deviation of the parameters, CC, and SNR are listed in Table 1. The results show that EF-LTS behaves very stably, with estimated parameters and criteria remaining invariant across executions. Table 1 also shows that EF-LTS achieves, on average, better correlation and SNR than RANSAC, making it more promising for IFSAR image registration. Figures 1 (c) and (d) present the obtained interferogram and correlation map after coregistering the images using parameters estimated by EF-LTS. The interferogram is the argument or phase of the dot product between the complex master image and the complex conjugate of the coregistered slave image. The correlation map is obtained by calculating the CC of three-by-three neighborhoods around each corresponding pixel position between the images. The interferogram and correlation map show that in stable areas such as buildings (the brighter area in Figures 1 (c) and (d)) and bare lands (upper right area), the interferogram fringe is very clear and correlation is very high. In residential areas (upper left area), the interferogram fringe is less clear and correlation is relatively small, possibly due to changes and scattering sensitivity to incidence angle changes. In other areas (mainly vegetated lands and parking lots), the interferogram is almost lost and coherence is very low due to significant changes during the temporal baseline. These results indicate that the registration matches ground truth very well, verifying the accuracy of the proposed EF-LTS.

4. CONCLUSION

Image registration estimates the geometrical warp between images. Many registration algorithms that perform warp estimation by fitting geometrical feature correspondences have recently been proposed for SAR. This paper investigates the appropriate parameter retrieval algorithm for feature-based SAR image registration. Since SAR images are acquired spatially or temporally separately, combined with influences from non-robust feature descriptors and matching algorithms, there are always unavoidable mismatches in constructed correspondences. Additionally, since SAR acquires target scattering with slant-range geometry that cannot be transformed to a central projection model, SAR geometrical warp cannot be modeled using global constant epipolar geometry as with optical images. However, we can conventionally approximate the warp function as a low-order polynomial when images are acquired over gently topographic areas with relatively short baselines. This indicates that we focus on global registration while neglecting local discrepancies. Therefore, to achieve accurate estimation, the retrieval algorithm should be robust to outliers and local image distortion.

Robust RANSAC is the widely-used retrieval algorithm in existing literature for SAR image registration. It performs estimation by randomly sampling an MSS to achieve a warp estimation, then checks the entire dataset to find correspondences consistent with the estimation to construct a CS. These steps are repeated iteratively until the probability of finding a larger CS drops below a threshold. However, this estimation strategy may magnify local distortion, resulting in estimation uncertainty and degrading global registration accuracy even when the largest CS is achieved. This uncertainty is validated by executing RANSAC 100 times on an IFSAR image pair, obtaining slightly different estimations with each execution. Additionally, an interesting phenomenon was observed: even for executions with the same CS cardinality, the obtained parameters were still different. This indicates that the extracted correct matches composing the CS are actually still varied; otherwise, the parameters would be stable because they are retrieved by simply LS fitting the inliers. All these observations demonstrate that RANSAC is unstable for SAR image registration due to its inappropriate estimation mechanism and loss function.

To enable stable and robust registration for SAR images, we propose extended Fast-LTS (EF-LTS), which conducts registration by fitting at least half of the correspondences to minimize squared polynomial residuals instead of fitting the MSS to maximize CS cardinality. Experiments on IFSAR image pairs demonstrate that the proposed algorithm works very stably and achieves, on average, better registration than RANSAC in terms of CC and spectral SNR. This algorithm can efficiently achieve stable estimation for any kind of 2D polynomial warp model with high robustness and accuracy, making it more appropriate and competent for SAR image registration.

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