COREGISTRATION BETWEEN SAR IMAGE SUBSETS USING POINTWISE TARGETS

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ABSTRACT

SAR image coregistration is a key procedure before starting InSAR time-series analysis. In this paper, we present a strategy to coregister SAR image subsets, instead of single SAR images, in attempt to improve InSAR time-series analysis. First, all potentially coherent image pairs are coregistered and divided into several image subsets, depending on a coregistration quality index or baseline information. Afterwards, offsets between point-wise targets, detected within the subsets, are estimated from incoherent mean amplitude maps. Then, these offsets are used to coregister the image subsets. The proposed method is implemented on two ENVISAT ASAR datasets and a clear coregistration improvement is found, which should lead to more accurate InSAR time-series analysis results.

1. INTRODUCTION

Time-series InSAR analysis techniques such as Permanent (Persistent) Scatterer InSAR (PS-InSAR) [1] [2] and Small Baseline Subset (SBAS) analysis [3] are widely used to precisely measure ground deformation patterns and trends at a high spatial resolution. It is well known that multi-image coregistration is the key procedure before starting time-series analysis. No matter whether PS-like or SBAS-like method is used, all the SAR images have to be coregistered and resampled onto the same grid of a single reference image (Master image). Mis-coregistration can severely reduce the interferometric coherence [4] and consequently result in incorrectly estimated ground deformation.

Conventional InSAR coregistration consists of three main steps [5] - [7]: 1) estimation of offsets between a number of tie patches with amplitude cross-correlation, 2) fitting of a polynomial wrap function to a set of tie-patch offsets, and 3) resampling of the slave images. Generally speaking, there are three difficult situations for multi-image coregistration of SAR data: 1) coregistration between long temporal and/or normal baseline pairs, 2) coregistration between SAR images spanning a strong deformation event, such as a volcano eruption or a large earthquake, and 3) coregistration between images with seasonal feature changes, for example with and without snow coverage.

To avoid coregistering long baseline SAR images, Refice, A. et. al. presented a method using a Minimum Spanning Tree (MST) to connect time-series SAR images [8]. Each interferogram (connection between SAR images) is weighted by its modeled coherence, and then the overall optimum tree is found, i.e. the MST connecting all the images. Coefficients of the polynomial warp functions are then transformed to map the coordinate of each image onto the Master image grid by inverting the incidence matrix of the MST. Similar idea is used in [2], except that all the small baseline SAR image pairs are coregistered instead of only considering the optimal combination like using MST. Then the polynomial wrap function coefficients w.r.t. the master image are estimated by the weighted least squares approach.

While MST and similar connection strategies may work well in some cases, we still face large gaps along either the temporal or normal baseline axis in many datasets. In other words, coregistration approaches between highly decorrelated scenes still need to be studied. The corresponding research is mainly divided in two branches. One is trying to detect features [usually pointwise targets (PTs)] in a single SAR image for better estimating the offsets [9] - [11], and the other one focuses on the geometric wrap function, with which only a few tie patches are needed [12] [13].

In this paper, we focus on the first branch of methods for long-baseline image-pair coregistration. We present a strategy to coregister between SAR image *subsets* instead of between single SAR images. First, we coregister all the potentially coherent image pairs and then separate the dataset into several image subsets, depending on the baseline information or on the coregistration quality. At this point, all the images within a single image subset are aligned with the conventional method, i.e. w.r.t. a temporal master image. And then, targets showing point-like features are detected with coherence analysis inside the subsets. Afterwards, the incoherent mean amplitude maps are used for measuring sub-pixel offsets on the detected targets between the subsets.

The proposed method is implemented on two test sites using ENVISAT ASAR images. One is a small volcano island (Jebel at Tair) in the southern Red Sea and the

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other is at the North Anatolian Fault (NAF) in eastern Turkey. For both test sites, long normal baseline (>500m) coregistration is unavoidable for the time series analysis. Moreover, for the Jebel at Tair test site, an eruption took place during the data acquisition span, and for the North Anatolian Fault site, seasonal snow coverage strongly complicates the coregistration situation. The strength of our method is validated and evaluated by showing the coherence improvement spanning the whole time-series dataset.

2. SMALL BASELINE SAR IMAGE COREGISTRATION

Selecting a master image and evaluating the best interferometric combination is an important topic in time-series InSAR analysis. Usually, the modelled coherence is used for these tasks. Depending on the spectrum shift and the bandwidths in azimuth and range dimensions, the geometric coherence can be estimated from the normal baseline and Doppler centre diversity. In addition, an exponential de-correlation model is commonly used for estimating temporal coherence [14][15]. Nevertheless, the in-situ truth can be far from the modelled coherence. For example, seasonal changes, snow coverage or a strong deformation event, such as a volcanic eruption, can cause strong deviations from the expected coherence. In such cases, modelled coherence may lead to a poor master-image selection and lead to a coherence loss during coregistration and interferometric combination.

It is impossible to evaluate the true coherence from interferograms in the initial stage of time-series InSAR analysis and therefore, defining a coregistration quality index is important. Since there is a close relation between amplitude cross-correlation and complex coherence [7], for a given number of initial match patches at the same locations in all the images, the amount of successfully coregistered match patches is a useful index to indicate the overall coherence between image pairs. To avoid influence from possible large incoherent areas (e.g. water bodies), we use the relative value. This means that all the image pairs are compared with the pair that has the highest number of remaining match patches to obtain percentages as the quality index.

Different MST obtained from the baseline information and from the relative coregistration quality index of the NAF dataset are shown in Fig. 1. The discrepancy between these two-connection strategies shows that the true coherence differs from what the coherence model predicts. This difference also suggests that the standard MST connection strategy may be far from optimal for many cases, as for any image-pair, there exists only one route to map the transformation coefficients w.r.t. the master image.

The transformation of images is usually modelled as a low degree polynomial, where we typically have a significant redundancy in number of match patches between two images. However, the spatial distribution of the good match patches should be considered as well. In other words, we may have enough match patches to constrain the polynomial model, but if they are all located in a small area, then the coefficient estimation will likely be unreliable. In this study, the concept of Dilution of Precision (DOP) [16] in GPS studies is adapted to take into account the distribution of the match patches.

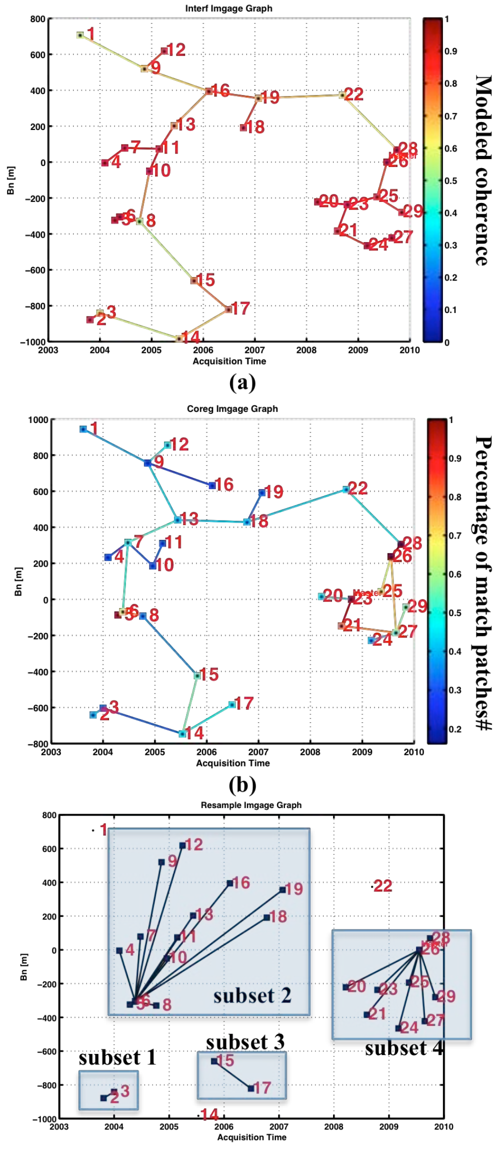

Figure 1, NAF dataset, (a) MST from baseline information, and (b) MST from coregistration. The color represents in (a) the predicted coherence and in (b) the percentage of successfully coregistered patches (w.r.t. a reference value). (c) shows the subset cluster selection.

We propose a coregistration quality test to reject unreliable coregistration pairs, a test that depends both the DOP and the cross-correlation of the match patches. Coregistration image pairs with offset standard deviation larger than a given threshold (in this study around 1/10 of pixel) and a DOP value exceeding one are rejected. It should be pointed out that this quality test is only to reject coregistration outliers. The image-pair that passes the test will be kept in the next stage of our method.

The quality test divides the Tair dataset into three subsets and one isolated image (Fig. 2). In particular, an onset of an eruption on 30 September 2007 is the main reason for the low quality index between subsets 2 and 3.

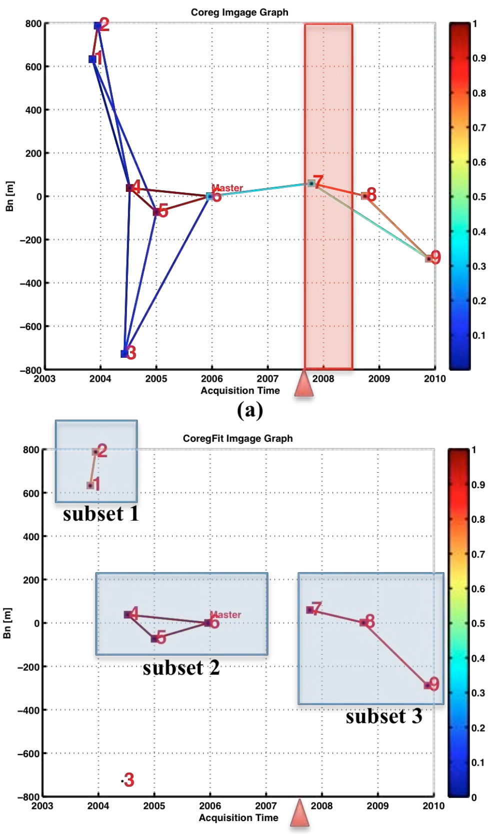

Figure 2, Coregistration graphs before (a) and after (b) the images were divided into three subsets, based on the quality test. The colour represents the relative quality test index as in Fig 1 (b). The red triangle indicates the start of an eruption in Sep. 2007 and the red frame in (a) shows the eruption period.

An alternative way of clustering images into subsets is to use a temporal and normal baseline thresholds directly, as we did for the NAF dataset (Fig. 1c). For this case, searching for enough stable PT match patches is the main issue, and therefore, small-baseline subsets are concerned.

The master image for each subset is selected from the overall coregistration image quality index. Afterwards, all the images are resampled w.r.t. the master image of each subset.

3. POINT-LIKE MATCH PATCH DETECTION WITHIN SMALL-BASELINE SUBSETS

After the initial coregistration, image subset clustering, temporal master-image selection, and the resampling of images within each subset, we face the problem of detecting good match patches between different *subsets*. Since the electromagnetic signature of a stable PT has been proved to be only slightly affected by the diversion of normal baselines [18], high amplitude cross-correlation can be expected from such targets.

In many time-series InSAR analysis, Pointwise Target Candidates (PTCs) are detected with amplitude dispersion D_A. However, the D_A value is only reliable when we have enough images[1]. The amount of images in our SAR image subsets is usually much smaller than the number we need for reliable amplitude analysis (>25). However, the PT detection for coregistration is different from the similar procedure for time-series analysis, in which the density of PTs is critical. For coregistration, we only need to detect the best PTs and to ensure that the PTs are spatially distributed over most of the scene.

Targets with point-like feature can be approximately detected by comparing the observed coherence with the estimated geometric coherence [19]. Since we already have several coregistered images, coherence analysis can be used to locate such targets within each subset. This method is especially useful when the number of images in a subset is limited. For each subset, the averaged decomposed coherence map associated with small baseline interferograms (here small means both normal and temporal baseline) is calculated. To ensure that good match patches are distributed all over the image, the analysis is carried out on image blocks. The selection threshold is loosened if there are not enough larger-than-one pixels on some blocks. In other words, the targets detected with coherence analysis may not be perfect pointwise one, but can show partially pointwise features, comparing with the decorrelating distributed targets. Moreover, for each coherence estimation window, only one pixel with the largest coherence is considered to prevent influence from side lobes.

Match patches detected with coherence analysis from the NAF dataset subset 4 are shown in Figure 4 (a) on the incoherent mean amplitude map. Below are details of the area marked by the red frame, showing the amplitude map (b) and the detected targets (c) with decomposed temporal coherence. The locations of the patches show agreement with strong reflective pixels in the amplitude map. Similar result was obtained from Tair dataset, even though only two or three images are available for each image subset.

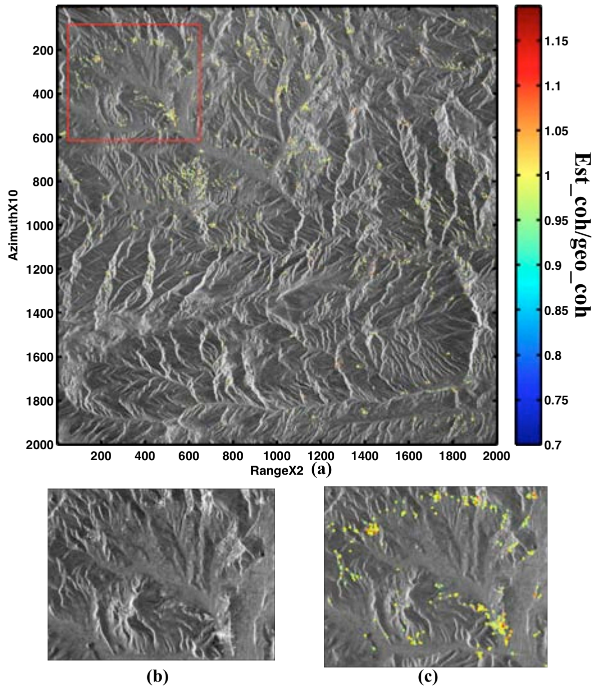

Figure 4 (a), Point-like match patches detected with coherence analysis from the NAF data, subset 4, plotted on the incoherent mean amplitude map. Below are the zoom-in views of the red frame. (b) shows the amplitude map and (c) is the detected targets with color.

4 COREGISTRATION BETWEEN SAR IMAGE SUBSETS

To coregister the different image subsets, we carry out the normal coregistration steps, as described in the introduction part, with the detected PT match patches. Since the speckle noise has been significantly reduced in the incoherent mean amplitude maps without spatial resolution loss, high amplitude cross-correlation can be expected. Fig. 5 reports the coregistration result between image subset 2 and subset 4 of the NAF dataset. The time span between these two subsets is more than 5 years and the normal baseline is about 300m. In (a), the cross-correlation histograms on match patches that passed the transformation model outlier test [20] are shown. The benefit gained by using the incoherent-mean amplitude map instead of single look SLC images is clearly demonstrated by this example. Around 5 times more patches passed the transformation model outlier test when the mean amplitude map was used, compared to the use of SLC images. Moreover, much higher cross-correlation can be obtained, suggesting higher precision offset estimates.

The coherence improvement is shown in Fig. 5 (b), the high coherence pixel (larger than 0.6) histograms from small-baseline and subset coregistration are reported. Very few pixels can be coherently observed in such a long time span in this rural region. Nevertheless, our methods increase this number from less than 4000 to more than 5000.

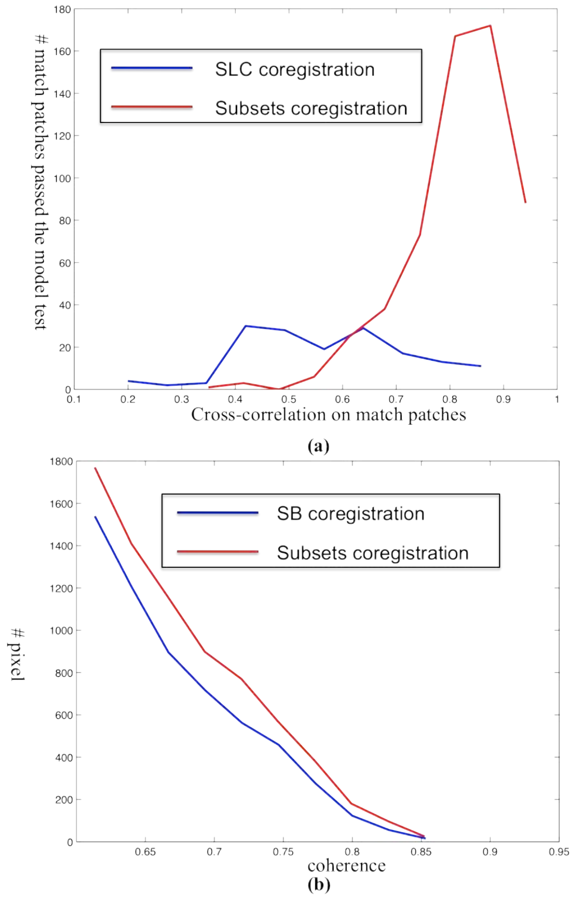

Figure 5 (a) comparison of match patches cross-correlation calculated from SLC SAR image (blue) and in-coherent mean amplitude image (red) for the NAF dataset. (b) high coherence (>0.6) pixel histograms from small baseline (blue) and subset (red) coregistration.

For the Tair dataset we compare the coregistrarion results from small-baseline coregistration and our methods on an image pair with 770m normal and two-year temporal baselines. The coherence improvement is shown in Fig. 6 (a). Besides the increasing number of high coherence pixels, the maximum coherence is also extended, showing the capability of our method in preserving coherent information for long-normal baseline image pairs. Similarly, in Fig. 6 (b) the coherence improvement between image subsets spanning the volcano eruption is shown. Since high coherence only remains in areas outside of the new lava, relatively few pixels show coherence value higher than 0.7. However, our method increased the total number of highly coherent pixels from 6480 to 7345.

It has to be noticed that in many cases, decorrelating distributed targets surround the stable pointwise targets. Since coherence is estimated using the spatial average operator, the improvement in coherence can be underestimated in the above examples.

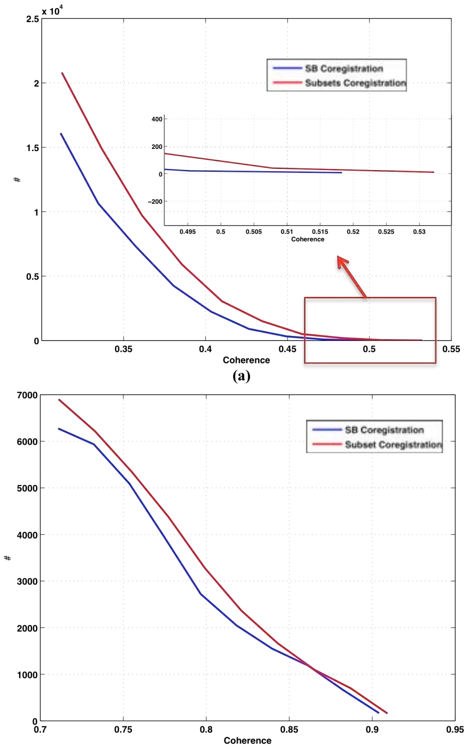

Figure 6. Coherence histograms comparison between small-baseline coregistration and subset coregistration for the Tair dataset, (a) subset 1 and subset 2, (b) subset 2 and subset 3.

4. CONCLUSIONS

A framework for time-series InSAR image coregistration is presented in this paper. The proposed coregistration quality index shows that modeled coherence does not always provide accurate information about interferogram quality in the initial stage of time-series analysis. For test sites where ground conditions can be complicated e.g. snow, lava, or strong ground deformation, a coregistration quality test is suggested for master-image selection, to search for suitable interferometric combinations, and to separate the data into image sub-sets.

We demonstrate clear coregistration benefits, on two non-urban test sites, by using detected PT match patches in image subsets and incoherent amplitude maps. The results prove the capability of our method in improving coregistration of datasets containing long spatial and/or temporal baselines and it should therefore be of help in many geophysical applications.

The main limitation of this strategy is that the coregistration and resampling procedures have to be carried out twice, leading to an increased computation burden. However, with the current computer capability, the extra processing time and storage space needed should not be a major limiting factor. Our future work will focus on integrating persistent scatterer candidates detection into the presented coregistration framework.

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