EuroVis Workshop on Visual Analytics (2016)
N. Andrienko and M. Sedlmair (Editors)

Visual Analytics for Persistent Scatterer Interferometry: First Steps and Future Challenges

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Abstract

In this paper, we introduce persistent scatterer interferometry *(PSI) as a new and promising application domain for Visual Analytics (VA). PSI studies changes of the Earth's topography by analyzing large time-varying point clouds that easily comprise hundreds of millions of data points. We briefly outline the PSI analysis workflow and present a VA approach to the first step in this workflow based on a flexible and interactive filtering mechanism. We further describe challenges for VA in PSI analysis. We want to engage the VA community in a discussion about potential VA solutions because we expect these solutions to not only advance PSI analysis but also provide valuable insights and contributions for the VA community regarding exploration and analysis of spatiotemporal data.*

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications—

1. Introduction

Persistent scatterer interferometry (PSI) analyzes synthetic aperture radar (SAR) data to study changes of the Earth's topography [CMCG*15]. Recently, continuous high-resolution global SAR data have become freely available with the launch of the Sentinel-1 satellites [Eur16] in 2014, offering new and exciting opportunities for large-scale and near real-time monitoring of surface deformations with PSI [FCF*15], e.g., in urban areas with vulnerable infrastructure or regions with known tectonic activity.

PSI analysis, however, is difficult. It involves three challenging main steps. First, persistent scatterers (PS) – measurement points with rather constant radar backscatter and stable phase characteristics – must be detected in the SAR data. PS provide reliable information about surface deformations undisturbed by effects of land cover and are usually found in urban or non-vegetated areas. To detect PS, large SAR data have to be examined that typically describe the topography of the Earth's surface for up to 0.4×10^9 geographic measurement points over 30 to 200 (sometimes irregular) time steps. Note that the number of time steps will increase continuously due to the new Sentinel-1 satellite mission. A second challenge is the subsequent analysis of the identified PS. To detect and study various types of surface deformations, the spatial distribution of the PS and changes of their position over time (displacement) must be considered simultaneously. Lastly, findings about surface displacement are compared to available ground truth – usually data from geodetic leveling surveys or global navigation satellite system (GNSS) stations – as a plausibility check and to account for uncertainties. The reference data have differing spatial resolution, temporal resolution, and data density, rendering the comparison of such heterogeneous data a difficult task. Currently, these challenges are only partially addressed by state-of-the-art PSI analysis [FCF*15, KKH*13].

In this short paper, we introduce a Visual Analytics (VA) approach for the initial step in the PSI workflow, the identification of PS in large SAR data (Section 3). The main feature of our approach is an interactive multi-criteria filtering, which offers users several mechanisms to determine filter thresholds and achieve a good trade-off between quantity and accuracy of PS points. However, it is our aim to develop an approach for the entire PSI analysis workflow to enable comprehensive detection, analysis, and validation of surface deformations. Therefore, we outline specific challenges for VA in the remaining steps of the PSI analysis workflow (Section 4). We expect that successful solutions to these challenges would not only advance PSI analysis but also provide valuable insights and contributions for the VA community regarding exploration and analysis of spatiotemporal data. The research presented in this paper is the result of an ongoing interdisciplinary collaboration between VA and PSI researchers in which a user- and task-based design approach [DKS*10] was adopted to gain a thorough understanding of the domain problem, elicit the involved challenges, and take first steps towards an appropriate VA solution.

2. Related work

In the PSI community, the standard tool for processing multitemporal SAR data is the open source Matlab©-based ***Stan**ford **M**ethod for **P**ersistent **S**catterers* (StaMPS) [HBSA12]. Its extension *viStaMPS* [SMR*13] offers basic plotting functionality and was not designed for comprehensive detection and validation of surface displacement.

In the last decade, the geovisualization and GeoVisual Analytics community has introduced many sophisticated solutions for visualization and exploratory analysis of spatiotemporal data [AA06, DMK05, DMT08]. They address, e.g., the analysis of spatiotemporal variation of mobile phone usage [AAB*10a], car and vessel movement data [DV10, AA13], exploration and prediction of crimes in the United States [AAB*10b, MRH*10, MMT*14], or various geoscientific applications [USKD12, DBS*11, Keh11, KLM*08, KSU*14]. Although these approaches provide plenty of inspiration for our work, we are not aware of VA solutions that could be applied or readily adapted to PSI analysis to facilitate comprehensive detection and analysis of surface deformations.

3. Visual Analytics for identification of persistent scatterers

PSI processing and the estimation of displacement is a nonlinear and user-driven procedure that can introduce large errors for noisy backscatter points. Results may differ significantly depending on chosen thresholds, filter settings, constraints and final interpretation. Thus the identification of valid PS with rather low errors in the SAR data is a crucial step in the PSI workflow. In this section, we present a VA approach to support this important task.

3.1. Background and design requirements

An important criterion for identification of PS is their temporal coherence [Han01]. The coherence is estimated in a preprocessing step along with other parameters such as terrain altitude and terrain motion. It measures the variance of the radar signal after removal of all other estimated parameters [FPR01]; the lower the variance, the higher the coherence and, hence, the quality of the PS. Usually, a rather restrictive minimum coherence threshold is used to identify valid PS. This threshold is the minimum required coherence for measurement points to be considered as PS and, thus, an estimate of reliability. The chosen threshold depends on the number of time steps in the data and on the problem in question, and is determined by statistical analysis of modeled (random) backscatter. This approach yields a relatively small number of highly reliable PS. For tasks like analysis of local displacement of single buildings, the resulting point density and distribution may not be sufficient. In this case, one may be thankful for any PS that can be found to prove displacement, even accepting increasing uncertainty up to a tolerable level. However, the properties of an appropriate trade-off between quantity and accuracy of PS cannot be specified a priori. Therefore, finding such a trade-off requires a lot trial and error; a difficult and tedious task with the current statistical approach.

To enable users to determine a good trade-off, VA must closely integrate the automatic statistical approach with interactive visual exploration. This is a challenging research question for VA. In our collaboration between VA and PSI researchers, we first focused on the interactive visual exploration part, eliciting the following design requirements (DRs):

DR1 Provide overview of spatial distribution of PS candidates.
DR2 Provide overview of distribution of selected parameters in parameter space.
DR3 Enable flexible multi-criteria filtering of PS candidates.
DR4 Allow users to base the filtering of PS candidates on the properties of user-selected geographic subsets.
DR5 Allow users to add PS candidates in selected geographic areas to improve data density on demand.

3.2. Approach and application example

Our concept allows users to conduct the initial statistical identification of PS with a rather relaxed minimum coherence threshold of 0.3. Our visual interface then enables users to assess the resulting set of PS candidates and identify the points that represent an appropriate trade-off between quantity and accuracy.

In the following, we illustrate our approach and its benefits with a specific application example: identification of adequate PS in the city of Stauffen in Breisgau, Germany. The SAR data for this area comprises 2.25×10^6 geographic measurement points and 39 time steps covering a two-year period from July 2008 to July 2010. Conducting the initial statistical identification with a coherence threshold of 0.3 yields 89500 potential PS. This result set has to be assessed to remove points that should not be considered in subsequent analysis. We can see in Figure 1 that the majority of the PS candidates are concentrated along roads and buildings. This makes sense because infrastructure does not change its reflectance characteristics much over time. Note that one can also observe a notable number of points in vegetated regions,

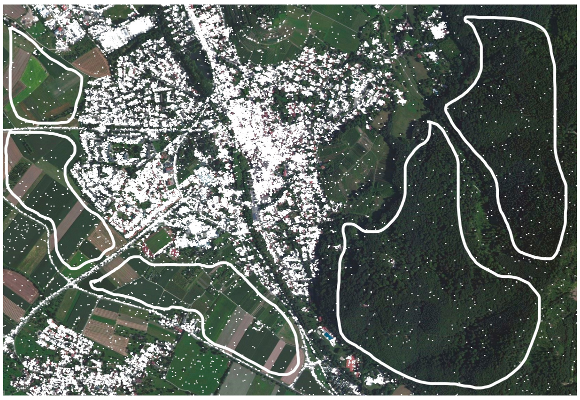


Figure 1: Spatial distribution of the PS candidates that satisfy a relaxed temporal coherence threshold of 0.3. The points in farming or forest areas (some indicated by white polygons) should not be considered valid PS and, therefore, need to be excluded from subsequent analysis.

such as forests or farming areas. Since the reflectance characteristics of such areas usually change significantly with the seasonal cycle, the points in these areas should not be considered valid PS in our scenario and, therefore, should not be included in subsequent analysis.

The visual interface comprises two linked and interactive components (Figure 2): a map that shows the spatial distribution of the measurement points (DR1) and a configuration and filter component. First, we want to exclude PS candidates whose coherence is still inadequate. We select the coherence parameter from the list of available parameters (Figure 2, A) by dragging and dropping it into the filter panel (Figure 2, B). For an overview of the distribution of the coherence in parameter space (DR2) a histogram appears (Figure 2, B1). We now have three options for determining an appropriate coherence range for the filtering (DR3): (1) manually adjusting the range sliders, (2) defining quantiles of interest, or (3) selecting geographic areas in the map to use the properties of the points within these areas, e.g., minimum or maximum, as filter criteria for the entire data set (DR4). In our example, we choose the latter to harness our knowledge about inadequate PS in forest areas. We select a forest area east of Stauffen by drawing a polygon in the map. Each selected area appears as an icon in the geography library of the filter panel (Figure 2, B2). To use the properties of the points in the selected area as filter criteria, we drag and drop the icon into the coherence histogram. We decide to use the maximum coherence of the presumably invalid PS within the selected forest area (approximately 0.4) as the minimum coherence threshold for the entire data set. To exclude not only data points with a low coherence but also with otherwise implausible parameters, we choose the relative point height from the parameters list as an additional filter criterion (DR3). We then apply the quantile filtering mechanism to set the valid range to 90% around the median of the height distribution (Figure 2, B3). The combination of these two filters enabled us to exclude many implausible PS across the entire Stauffen area while still retaining a large number of promising PS for subsequent analysis.

The feedback from the PSI experts in our collaboration is very encouraging. They emphasize that the versatile, easy definition and combination of various filters as well as immediate visual feedback enables them to readily identify adequate PS. Furthermore, the approach provides them with the flexibility to adjust the filtering to varying demands on quantity and accuracy of the PS and, hence, different analysis tasks.

Note that DR5 is not yet included in our approach. To add PS candidates to user-selected geographic regions requires tight integration with the automatic statistical approach – a VA challenge we are currently working on. Successfully addressing DR5 will offer new exploration mechanisms to users. For example, they may start with a small number of high-quality PS and gradually increase the number of PS in sparse areas. The filtering mechanisms already provided in our tool will enable them to assess and refine the added PS candidates.

4. Remaining challenges for Visual Analytics

In this Section, we outline the main challenges for VA in the remaining steps of the PSI workflow.

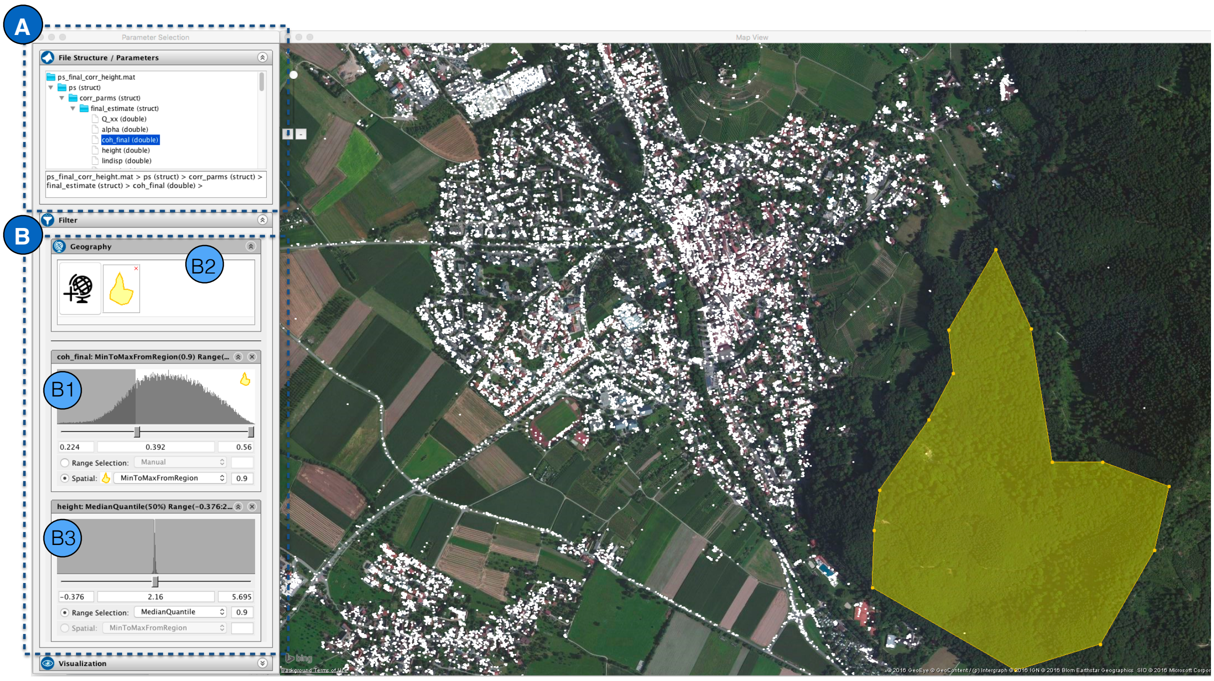
4.1. Challenges in the detection and analysis of surface displacement

At this stage of the PSI workflow, tens of thousands up to millions of PS must be analyzed regarding their development over time. In particular, two analysis questions provide interesting challenges for VA.

Where in geographic space can displacement be observed?

Our collaborating PSI experts approach this task by plotting the linear displacement of the PS and visually scanning for significant displacements. This straightforward approach works well for comparatively large-area displacements that persist over the entire time span covered by the data. In contrast, small-area or sporadic displacements are easily overlooked although they may also provide valuable information about surface deformations. This poses the following challenges for VA:

Challenge 1: How to integrate automatic detection of surface displacement events, irrespective of their duration and temporal occurrence, with interactive exploration to harness the PSI experts' domain knowledge in the detection process.
Challenge 2: How to prevent users from overlooking small-area or sporadic displacements?



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● Spatial: MinToMaxFromRegion 0.9

height: MedianQuantile(50%) Range(−0.376:2...

−0.376 2.16 5.695

● Range Selection: MedianQuantile 0.9

○ Spatial: MinToMaxFromRegion

Figure 2: Visual interface of our approach. The spatial distribution of PS points in the Stauffen area after applying two filters is depicted in a map. Various filters can be defined and combined in the configuration and filter component (left). It comprises a list of available parameters (A), a filter panel (B), and a visualization panel (not shown). Parameters for filtering are selected by dragging and dropping them from A into B. In this example, the filter criteria are the temporal coherence (B1) and the relative point height (B3). The minimum threshold for the coherence is determined by the maximum coherence value of the (now excluded) points in the polygon (see map and geography library B2).

What different types of displacement can be observed?

For a thorough assessment of displacement it is not only important to know where and when it occurs but also to distinguish different types, such as linear, periodic, accelerating, or decelerating displacement.

Challenge 3: How to enable users to use their expert knowledge in the definition and detection of known displacement types? How to enable detection of unexpected types?
Challenge 4: How to provide a comprehensive overview of the detected types? Where and when do they occur? How do they look like?

4.2. Challenges in the comparison to reference data

To validate any insight gained, the PS data must be compared to leveling and GNSS ground truth. However, the comparison is difficult because (a) the reference data have been collected at only a few selected and irregularly distributed geographic coordinates and points in time, and (b) the coordinates and acquisition dates of ground truth and PS data usually do not match.

Challenge 5: How to match the heterogeneous reference data with the PS data?

Challenge 6: How to support in-depth comparison in three geospatial dimensions plus time?

5. Conclusion and future work

The aim of this paper was threefold: (1) Introduce PSI analysis as a new and promising application domain for VA, (2) present a flexible and interactive filtering mechanism to support the important step of PS selection, and (3) describe the remaining challenges in PSI analysis to engage the VA community in a discussion about potential VA solutions. In future work, we will address the remaining challenges outlined in this paper. Together with PSI experts, we will investigate existing machine learning and data mining techniques to determine to what extent they are applicable to the challenges of PSI analysis, or if adapted or new methods are required. Furthermore, we will continue our interdisciplinary collaboration to integrate appropriate automated analysis methods with interactive visualization to facilitate exploration and comparison of surface displacement in space and time.

Acknowledgements

Parts of this work have been funded by the Helmholtz-CAS Joint Research Group (HCJRG-117).

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