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HYBRID INSAR PROCESSING FOR RAPIDLY DEFORMING PEATLANDS AIDED BY CONTEXTUAL INFORMATION

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ABSTRACT

We present a novel InSAR processing scheme which combines point scatterer (PS) and distributed scatter (DS) approaches in a hybrid framework along with contextual information about the environment under study. Data such as land parcel divisions, precipitation and temperature are integrated into the processing pipeline in order to produce accurate deformation time series estimates of the Dutch peatlands. In addition to these steps, a segmented processing scheme is introduced to manage irreversible losses of coherence in the interferogram stack. Initial results show a promising agreement with in-situ ground truth measurements gathered by extensometer readings of shallow surface deformation.

1. INTRODUCTION

A vast amount of the Dutch agricultural sector is built on drained peatlands which provides fertile soil for crop production and grazing. This land is intensively farmed in order to support the country's large amount of food production. In recent years, scientists have become concerned by an increasing amount of land subsidence strongly believed to be linked with the active drainage of these peatlands. InSAR is a uniquely positioned technology to monitor this subsidence on a national scale with high spatial and temporal coverage.

Unfortunately, the environment poses several challenges which have so far prevented the successful application of time-series InSAR for monitoring the subsidence of the region. Low, non-stationary levels of coherence and rapid soil deformation cause large fluctuations in the parameters to be estimated by the functional and stochastic models. The high amount of noise combined with highly rapid soil movements make temporal phase unwrapping an extremely error-prone process, as it is very difficult for algorithms to distinguish between noise and real deformation, or correctly identify large real deformations which exceed the phase ambiguity threshold. We refer to these types of errors as (integer) *cycle-slips*. Additionally, seasonal changes in coherence result in the almost complete loss of information in the spring and summer months, as shown by the red box in Fig. 1. This splits the time series of observations into adjacent but non-contiguous parts, with no apparent way to interconnect the coherent periods together; we refer to this scenario as a *loss-of-lock*, which effectively creates a real-valued offset in the time series.

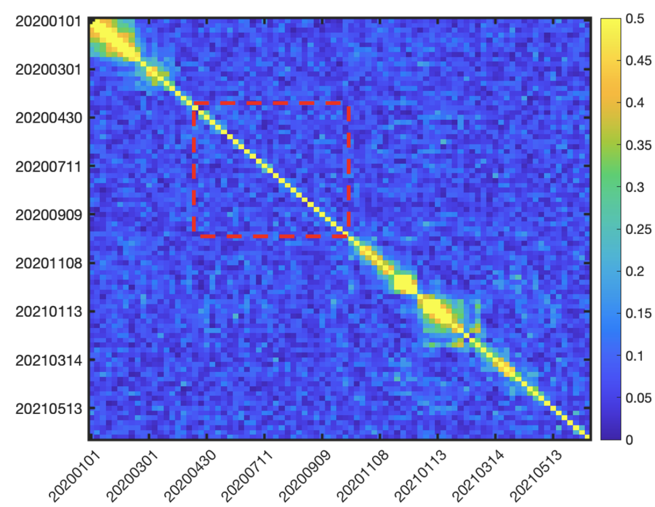


Fig. 1: Observed coherence matrix of a representative parcel in Zegveld, The Netherlands, as obtained by Sentinel-1 ascending track 088.

To combat the effect of cycle slips and loss-of-lock, we introduce a new processing framework designed to maximize the amount of information available to the algorithms. This is accomplished by suppressing noise as much as possible, using both PS and DS observations, integrating additional contextual information about the scene and driving mechanisms into the workflow, and dividing the time series into segments of sufficient coherence which are used to fit a deformation model.

2. METHODOLOGY

2.1. Parcel-Based Multilooking

Spatial multilooking is performed in DS processing to suppress noise and is typically accomplished by applying a boxcar filter to the interferogram. It is also common to employ a statistical test on the pixel amplitudes to determine groups of so-called statistically homogeneous pixels (SHPs) or "brotherhoods" [1]. This test assumes that pixels which exhibit similar amplitude statistics will also exhibit similar phase statistics, thereby preserving ergodicity. While very useful, this approach does have some shortcomings: a) the SHP test can remove many pixels from the averaging filter, significantly lowering the equivalent number of looks; and b) there is no guarantee that the pixels being averaged really belong to the same object or surface. We contend that the placement of the averaging filter with respect to its geolocation is an often overlooked aspect to multilooking which can greatly influence the success of an InSAR processing scheme. Whenever possible, multilooking boundaries should be made to follow object or surface divisions present in the scene to help ensure ergodicity and representativity while maximizing the number of equivalent looks. In our case, the Dutch peatlands are segmented into large rectangular parcels of land which are surrounded by drainage ditches. In general, the groundwater level and land cover within a parcel is consistent. These parcels provide us with a natural way in which to segment the interferogram into representative multilooked regions. The full coherence matrix of each parcel may then be computed, and an equivalent single master (ESM) phase estimation is performed using the EMI method described in [2].

2.2. Mixed PS-DS Processing

The multilooking scheme described in Section 2.1 is used to condense each parcel to a representative point. These DS "points" are subsequently treated as secondary PS points in the Delft Persistent Scatterer Interferometry (DePSI) system [3]. This has several major advantages to using a pure DS processor: atmospheric phase screen (APS) and trend removal

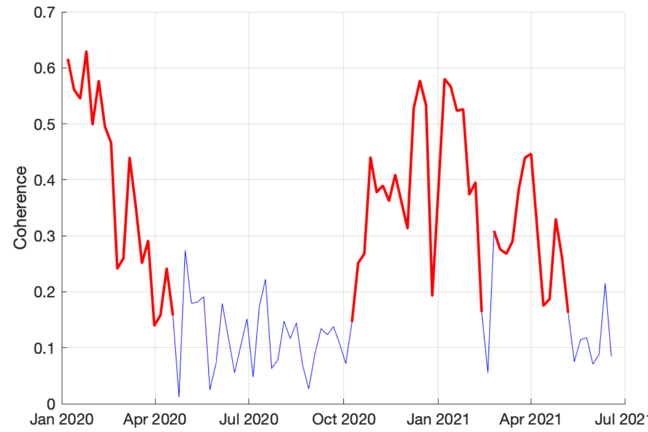


Fig. 2: Observed daisy-chain coherence of a representative parcel, divided into three segments (red bold lines) of at least 10 consecutive epochs with $\hat{\gamma}_{DC} > 0.1$ in Zegveld, The Netherlands, obtained by Sentinel-1 track Ascending 088.

can be done using a robust network of primary PS points, and mixed PS-DS arcs can be formed, which allows us to estimate how open ground is moving relative to built infrastructure points.

2.3. Machine Learning Aided Phase Unwrapping

The Dutch peatlands are characterized by rapidly moving soft soils which can seriously hinder temporal phase unwrapping, as deformations exceeding the phase ambiguity threshold can occur within even the shortest overpass periods (6 days, Sentinel-1) [4], [5], which standard techniques are unable to cope with [6], [7]. A novel phase unwrapping technique which employs a recurrent neural network (RNN) to anticipate large shifts in the ground level based on environmental information (temperature, precipitation and day of year) is implemented, allowing us to track the ground movement during strong deformation events [5]. The algorithm works by stepping through each epoch and assessing the relative likelihoods of upward vs. downward motion with respect to the previous epoch, based on the RNN output and the observed wrapped phase change.

2.4. Segmented Processing

Distributed scatterer observations of the Dutch peatlands systematically lose coherence during spring and summer months, as shown in Figs. 1 and 2. This long-term loss of coherence effectively constitutes a loss-of-lock event, essentially cutting the time series into non-contiguous parts. Repeated losses of coherence will inevitably lead to poor results as phase unwrapping errors and noise systematically accumulate and can cause significant problems in the interpretation of a phase displacement time series [6, Fig. 6], [8, Fig. 1].

One potential solution is to divide the time series into segments based on the coherence levels, process the segments individually, and facultatively use a deformation model to fit the results together. We illustrate how this may be accomplished by segmenting the time series based on the estimated daisy-chain coherence ($\hat{\gamma}_{DC}$), and fitting the time series back together using a seasonal plus linear model. One easy way to segment the time series is to stipulate that a segment must contain a minimum number of consecutive epochs with $\hat{\gamma}_{DC}$ greater than a threshold value. An example using a minimum of 10 epochs with a threshold of $\hat{\gamma}_{DC} > 0.1$ is shown in Fig. 2. These segments are initially treated as separate time series and unwrapped using the scheme described in Section 2.3. An annual seasonal plus linear model is scaled to fit the segments by minimizing the mean square error between the segments and the model. The segments are then shifted vertically to align with the model. Finally, estimates for the low-coherence epochs (which were not included in a segment) of the time series are produced by forcing the ambiguity level which most closely matches the deformation model, in similar fashion to standard DePSI processing [3].

3. RESULTS AND DISCUSSION

Results of the segmented processing scheme are shown in Figure 3, using observations by four Sentinel-1 tracks from January 2020 to July 2021 of a typical grassland parcel in Zegveld, the Netherlands. A very good agreement with ground truth measurements from the same location can be observed. While some phase unwrapping errors are likely present, for instance in November 2020 in Fig. 3a, their effect on the overall quality of the time series is minimized by the segmentation scheme.

While the segmentation parameters (minimum number of consecutive sufficiently coherent epochs, coherence threshold) chosen for this study are rather conservative and result in a significant number of observations being omitted, the key is to provide enough data for the model-fitting to be successful. In Figs. 3a, 3b and 3d, while data from the spring and summer months is omitted from the initial segmentation, there is enough to accurately estimate the deformation model and reject significant amounts of noise from the time series. In Fig. 3c, significantly fewer epochs are able to be used and the modeling is less accurate.

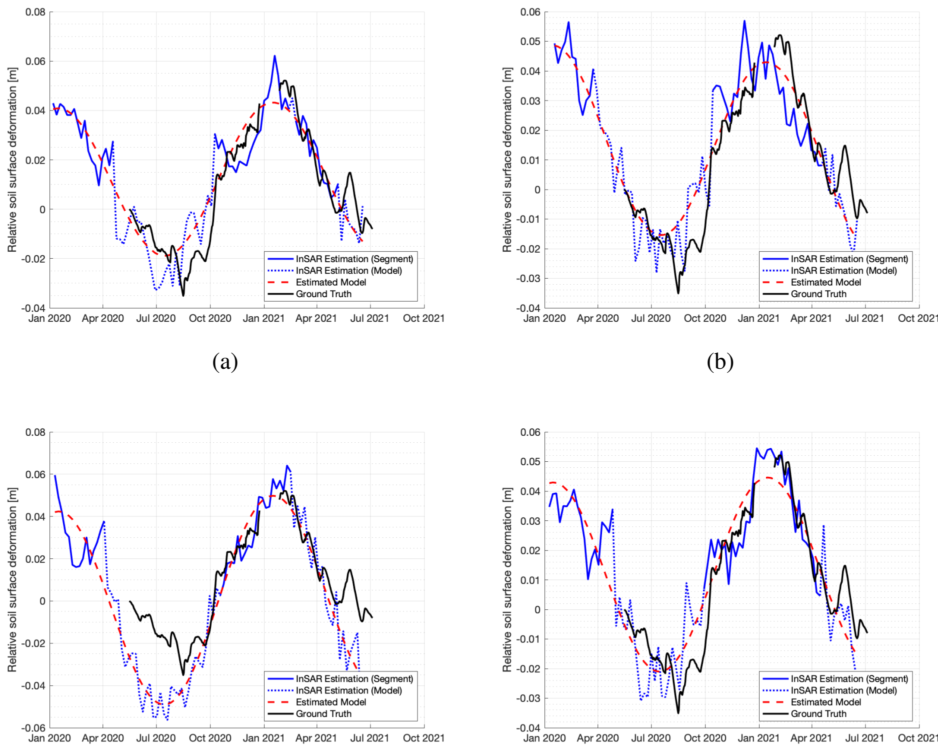
While the daisy-chain approach can identify the loss of both short and long-term coherence in the spring/summer months, in some cases, short term coherence may be lost but long-term coherence may still remain in alternative interferometric combinations which could be made use of in the future by considering the full coherence matrix in the segmentation scheme.

Fig. 3 shows that the simple seasonal plus linear model is effective for estimating the relative vertical shifts between segments as a proof of concept, and the success of the segment reconnection relies on choosing an appropriate model. In the future, this model can be replaced with a more sophisticated model as we learn more about the expected behaviour of the region. For instance, a kinematic model based on the parcel groundwater level could be used as more advanced groundwater models become available, or a data-driven approach based on cumulative InSAR observations of similar areas can be used to derive a model, as demonstrated in [8].

4. CONCLUSION

The environment under study has a great influence on what type of processing schemes are successful and must be taken into account when performing InSAR time series analysis. In this work, we show how divisions present in the terrain can be used to guide the multilooking scheme of a DS processor to minimize noise and losses of ergodicity. Additionally, integrating these DS observations into a PSI framework can be a very powerful tool, which enables APS and trend removal for both the PS and DS points in the scene. The environment again plays a crucial role when performing phase unwrapping, as rapid uplift caused by precipitation can create cycle slips if not taken into account. Finally, we show how loss-of-lock events which occur when coherence is repeatedly lost in the spring and summer months can be bridged by means of fitting a deformation model to individually-unwrapped highly coherent segments.

Our initial results indicate that maximizing the information available to the InSAR processor, including both PS and DS InSAR observations, but also contextual information such as parcel divisions, precipitation and temperature, leads to a



(a) (b)

(c) (d)

Fig. 3: Estimated relative deformation using segmented processing compared to ground truth measurements for Sentinel-1 tracks: (a) Ascending 088, (b) Ascending 161, (c) Descending 037, and (d) Descending 110. Solid blue line: coherent segments unwrapped using RNN-aided algorithm. Dotted blue line: incoherent segments estimated using model. Dashed red line: estimated model. Solid black line: ground truth (Note: the gap in the data in Jan. 2021 was caused by uplift which exceeded the range of the extensometer scale and could not be recorded).

more accurate and reliable result. This is shown by the initial results of this hybrid processing scheme, which are very promising. To our knowledge, the InSAR displacement estimates we have obtained are the most accurate yet of the region of Dutch peatlands under study. For the future, we plan to continue in this vein and integrate groundwater and soil type information into our processing framework.

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