SUPERVISED MULTI-TASK LEARNING FOR TRACKING INLAND GLACIER FLOWS USING SENTINEL-1 TOPS DATA

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ABSTRACT

Multi-swath SAR interferometry is a powerful tool for assessing sub-wavelength changes over large-scale areas. The azimuth variation of the line of sight (LOS) induces phase jumps between adjacent bursts in the interferograms which contain useful information about the motion. In this work, we present a multitask convolutional neural network that simultaneously decouples the interferometric phase due to displacements in the LOS direction from that due to displacements in the along-track direction, and predicts a proxy for the along-track displacement. We show results using a single pair of Sentinel-1 acquisitions over the inland region of Greenland, where glacier flows occur in the winter season within the revisit time

Index Terms— Synthetic Aperture Radar (SAR), SAR interferometry (InSAR), Sentinel-1, TOPS, surface displacement, Deep Learning (DL), Multitask learning (MTL), convolutional neural networks (CNNs)

1. INTRODUCTION

Scanning Synthetic Aperture Radar (ScanSAR) [1] and Terrain Observation by Progressive Scans (TOPS) [2] are the two most widely used multi-swath SAR systems. They both exploit the burst mode technique to increase the ground coverage by cyclically sweeping the elevation antenna beam to illuminate different ground regions, called subswaths. Each subswath is a sequence of partially overlapped SAR image units, named bursts. Multi-swath SAR systems are often used in differential SAR interferometry (DInSAR) mode for tracking large-scale displacements over non-stationary scenes, e.g., areas containing glaciers or affected by earthquakes.The main challenge of using the burst mode systems is the retrieval of interferometric outputs along the edges of the bursts. The azimuth variation of LOS introduces phase jumps between adjacent bursts, which makes phase unwrapping difficult. Ideally, an unwrapped phase correction should be created to remove the discontinuities in the interferograms and should be sufficiently accurate to be reapplied to the unwrapped data in a later step for proper surface displacement estimation. If the processing bandwidth is large enough to observe the same target twice on the ground, the phase jumps can be compensated by implementing a 2-look multi-swath mode [3], but in the case of 1-look multi-swath systems such as Sentinel-1 (S-1), other solutions are needed to decouple the displacements in the LOS direction from those in the flight direction. S-1 is the first of the five missions designed in the frame of the EC/ESA Copernicus Programme [4]. Each satellite flights in a near-polar, sun-synchronous orbit with a 12-day revisit time and consists of a C-band SAR instrument that mainly operates in TOPS mode, providing 1-look data with a 250 km swath at a ground resolution of 5×20 m in range and azimuth, respectively. In S-1, the azimuth variation of the LOS is due to the electronic rotation of the antenna beam from backward to forward in the flight direction. As a result, the antenna steering creates a variable sensitivity to the surface displacement along the azimuth direction that combines the along-track (AT) and across-track, or zero-Doppler (ZD), phase contributions. In this paper, we frame the coupling of AT and ZD phase contributions as a phase source separation problem and we propose a convolutional neural network (CNN) to jointly separate the AT and ZD phase contribution and reconstruct the associated AT deformation. The paper is structured as follows. Section 2 reports two selected published works used for comparison in the experiments. The proposed methodology, described in Section 3, is based on the synthetic dataset generation, the strategy for patch extraction and the structure of the selected CNN. Section 4 presents the results on a real S-1 IW subswath and compares the CNN's prediction with the state-of-the-art algorithms presented in Section 2. Section 4 presents a brief outlook and the future development of the presented methodology.

2. RELATED WORK

In this section we describe two state-of-the-art techniques used to compensate for the phase jumps introduced by the antenna steering in S-1 TOPS mode. Both methodologies exploit the information hidden in the overlap areas of two consecutive bursts to retrieve an accurate estimation of the along-track displacement. In [5], the authors suggest the usage of a speckle tracking technique to reduce phase discontinuities and increase coherence. An ad hoc Incoherent Cross-

Correlation (ICC) algorithm is developed for non-stationary scenarios, which aims at tracking the speckle signal with adaptive spatial averaging. The local offsets measured using the ICC are used to update the offset matrices and, as a result, the interferometric phase preserves the sole displacements in the LOS direction. The along-track displacements can be retrieved by subtracting the phase retrieved when applying the speckle tracking from the interferograms estimated using the standard interferometric chain. The technique described in [5] performs well in scenarios with high interferometric coherence, but introduces artifacts at burst edges when the coherence degrades. The same problem is investigated from a different perspective in [6], where the authors observe only the differential interferograms of the overlapped areas. In particular, they propose an image inpainting technique to fill the gaps in between, providing a proxy for the phase and motion in the along-track direction. Although the information in the overlaps is reliable, the usage of inpainting implies a relevant computational time and might be meaningless in the gaps. Additionally, the suggested methodology requires a 2-D phase unwrapping, which might be subject to errors in complex scenarios.

3. METHODOLOGY

Fig. 1 shows the flowchart of the supervised convolutional neural network for the interferometric phase source separation problem.

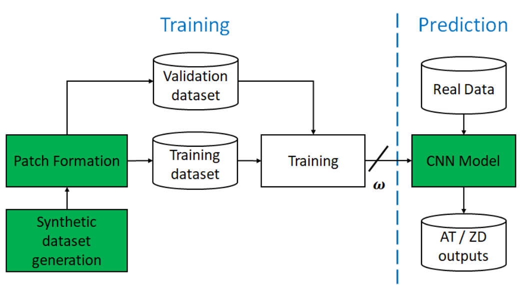

Fig. 1. Workflow of the proposed CNN. Blocks in green highlight the innovative aspects of the presented work.

In the following, the three blocks shown in green in 1 are described in three separate sections. We refer to [7] for the detailed implementation.

3.1. Synthetic dataset generation

For the generation of the interferograms, we induce a user-defined desired coherence and the surface displacement as a noise-free phase in the secondary acquisition. Due to the complexity in real nonstationary scenarios, we suggest the synergy of multi-source external displacements. In particular, we recommend the usage of online ice velocity maps produced by applying the offset tracking technique over Greenland [8] together with mathematical displacement maps generated using the Okada model [9].

3.2. Patch formation

Given a set of synthetic TOPS interferograms using the approach described in Section 3.1, we extract patches based on the geometric properties of S-1 TOPS de-bursted subswaths. In particular, each patch is centered in the phase jump, and the patch size is chosen to ensure the final aggregation of the predicted patches and depends on the multilooking window applied for the interferogram generation.

3.3. CNN model

The proposed CNN, drawn in Fig. 2, is a modified version of the standard U-Net model for multitask learning purposes. Four input features, i.e. the real and imaginary parts of the interferometric phase ϕ, the coherence ρ and the Doppler centroid frequency map f_{dc} are jointly used to estimate three output features in two interconnected branches: the (a) along-track and (b) zero-Doppler phase, respectively indicated as $\hat{\phi}_{at}$ and $\hat{\phi}_{zd}$, and the (c) along-track displacement $\hat{u}_{at}$. In particular, the proposed CNN considers a common encoder-like block that splits the output feature maps at the bridge layer into two decoder-like blocks, called phase decoder and along-track motion decoder, respectively. The former predicts the AT phase $\hat{\phi}_{at}$, then compensates for the input interferometric phase ϕ for estimating the ZD phase $\hat{\phi}_{zd}$. The latter reconstructs the AT displacement map $\hat{u_{at}}$. The blocks highlighted in yellow in Fig. 2 refer to the interconnections between the branches. In particular, the $T_{at}\{\cdot\}$ operator followed by the wrapping block $(\cdot)_{2\pi}$ reconstructs the AT phase from the estimated AT displacement, $\hat{u}_{at}$ by using the doppler centroid frequency f_{dc}. A minimization problem can be employed to guarantee the consistency between $\hat{u_{at}}$ and $\hat{\phi}_{at}$.

4. EXPERIMENTAL RESULTS

Training and test stages have been conducted over Greenland by geographically separating a set of ten Sentinel-1 acquisitions in the inland region. The training data set has been created considering nine out of ten footprints and inducing on the secondary SAR image the multi-source displacements described in Section 3.1 and following the patch formation strategy described in Section 3.2. The remaining footprint has been used only for testing the network and in particular over there a 12-day real interferometric pair has been selected and processed using the standard steps in SAR interferometry without global coregistration refinements. Results using a real interferometric pair acquired in a time frame of 12 days during the Winter season over an inland region in Greenland are summarized in Figure 3. We show a strip from one of

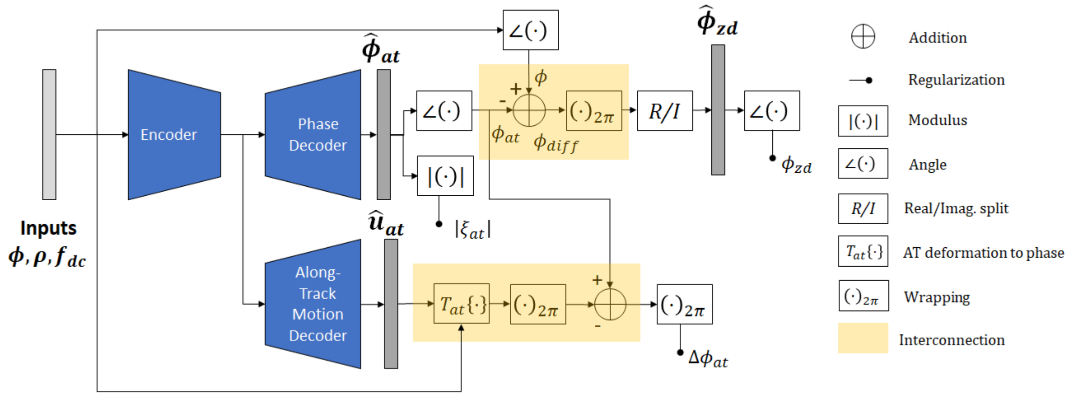

Fig. 2. Proposed network architecture. Yellow blocks address interconnections that guarantee the interaction between the upper and lower output branches and the upper output and input.

the three S-1 IW subswaths associated with the interferometric pair. Although in Fig. 3(a) the coherence over an inland region of Greenland is on average close to 0.7 and almost uniformly distributed in space, the associated interferometric phase presents discontinuities in the azimuth direction. From left to right in Fig. 3(b) we notice that phase jumps at the beginning of the strip look larger than the ones at the end. Accordingly, a larger along-track displacement is foreseen at the beginning of the strip. Fig. 3(d)-Fig. 3(f) report the three predictions of the proposed neural network, i.e. from top to bottom the ZD phase $\hat{\phi}_{zd}$, the AT phase $\hat{\phi}_{zd}$ and the AT displacement map $\hat{u}_{at}$. In particular, each output feature is obtained using the aggregation strategy briefly discussed in Section 3.2. As expected, the proposed CNN is separating the input phase of Fig. 3(b) in two contributes, i.e. the quasi-continuous ZD phase in Fig. 3(d) that contains the displacements occurring in the LOS direction and the AT phase in Fig. 3(e) that shows the phase jumps occurring at mid-overlap of the mosaicked phase. The predicted along-track motion in Fig. 3(f) is linked with the density of fringes in the overlap areas and is intended as an approximation at mid-burst because of the different sensitivity along the TOPS burst. In addition, two sample patches of 256×256 pixels, denoted as *(i)*, *(ii)* in Fig. 3(b), are selected with white squares and processed using the two methodologies described in Section 2. The predicted ZD phases are compared with the result of the proposed neural network in Fig. 4. Given the phase jumps in the input data, presented in column (a), the phase correction applied using the proposed CNN in column (d) is finer than the ones applied using speckle tracking, reported in column (b), and image inpainting, shown in column (c), which do not fully mitigate the discontinuities. Speckle tracking introduces noisy jumps over the right overlap of patch *(i)* and on both the left and right overlaps of patch *(ii)*. Thanks to its DEM-based implementation, image inpainting appears more robust, but we can still observe a phase jump residual on the left overlap of patch *(ii)*.

5. CONCLUSION

This paper presents a supervised multitask learning approach to separate the phase contributions due to zero-Doppler along-track displacements in TOPS interferograms. This can be used to retrieve the along-track deformation of inland glacier flows. The proposed approach is a promising alternative to existing speckle tracking approaches, which are much less sensitive to this type of change. The scientific impact of this work could be the ability to map Greenland with unprecedented accuracy using a single S-1 interferometric pair.

6. REFERENCES

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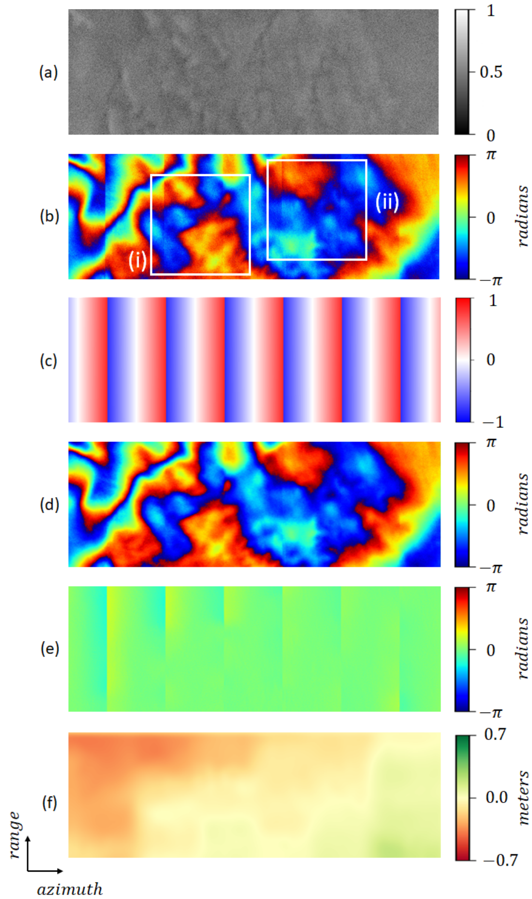

Fig. 3. Input features extracted from a real interferometric pair over Greenland and predicted output features. From top to bottom: (a) coherence ρ, (b) interferometric phase ϕ, and (c) Doppler-centroid frequency f_{dc}, predicted (d) zero-Doppler phase $\hat{\phi}_{zd}$, predicted (e) along-track phase $\hat{\phi}_{at}$, and predicted (f) along-track displacement $\hat{u}_{at}$. Two sample patches *(i)*, *(ii)*, of 256×256 pixels are marked with white squares.

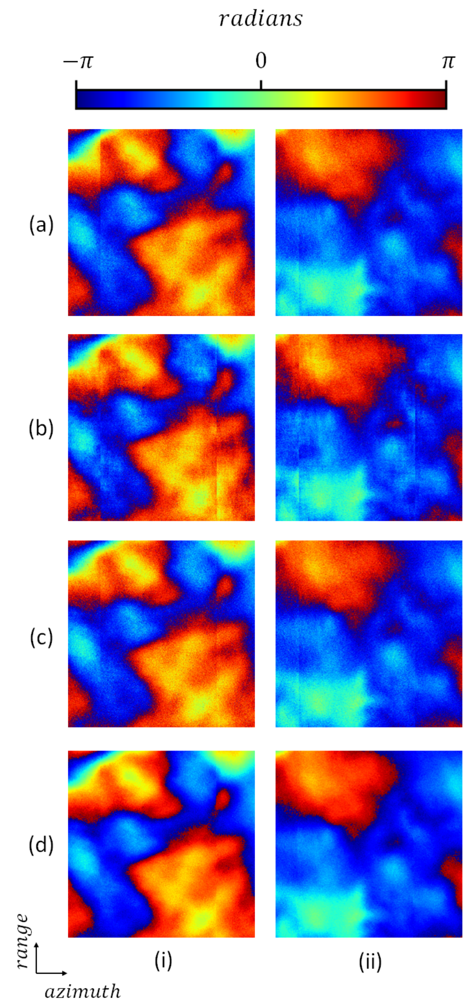

Fig. 4. Predictions using different methodologies (rows) on different patches (columns) identified in Fig. 3. From top to bottom: (a) ϕ, and $\hat{\phi}_{zd}$ reconstructed using (b) speckle-tracking [5], (c) image inpainting [6], and (d) the proposed architecture.

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