Unlocking onboard SAR processing: focusing and ship detection on Sentinel-1 IW data

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Onboard SAR data processing

Synthetic Aperture Radar (SAR) systems can provide high-quality images at a sub-meter resolution regardless of lighting and weather. However, SAR data acquired onboard the spacecraft consists of raw signals which are nearly uninterpretable to the human eye. To produce a recognizable image and to enable further data processing, the so-called focusing procedure must be performed. This is a demanding computational task currently performed on the ground in dedicated processing facilities, hindering real-time surveillance capabilities.

By unlocking onboard SAR processing capabilities, EO data producers can generate actionable information directly on the satellite. This will increase the autonomy of satellites, enhancing their functionalities and enabling new concepts of operations, such as real-time monitoring (i.e., event detection).

Overview

This work demonstrates the possibility of enabling onboard processing of SAR data in real-time through the adoption of an innovative focusing technology coupled with object detection, using limited computational resources. Our approach aims to provide a coarse focused product onboard to unlock real-time monitoring capabilities, complementing the ground-based detailed focusing algorithms.

The focusing algorithm transforms the Level-0 raw signal into Level-1 Single-Look-Complex (SLC) data. It consists of a two-layers hybrid architecture: a traditional Fast-Fourier Transform (FFT) algorithm for range processing and a Deep Neural Network (DNN), trained to solve the azimuth processing task, which provides scalability and modularity benefits. After focusing, an object detection network is trained to detect the presence of ships in the SLC data.

The whole processing chain has been optimized and deployed on different embedded devices, including NVIDIA Jetson Nano, and NVIDIA Jetson Xavier, to demonstrate the feasibility of running the overall pipeline onboard the future generations of SAR missions.

Traditional SAR image formation

Differently from optical data, the direct visualization of raw SAR products is not meaningful and does not provide immediate information about the imaged region. There is the need of applying signal processing techniques to process the phase history of the acquired data and retrieve a 2-D image scene of the mapped area.

Dealing with this problem directly in the time domain requires a high computational effort, hence several SAR image formation algorithms work in other domains. Algorithms working in frequency domain exploit fast convolutions based on Fourier transform (FFT) with a noticeable computational gain. Among those, the Range Doppler Algorithm (RDA) represents one of the best trade-offs between accuracy, efficiency and generality. As its name suggests, most of the processing steps are carried out in the Range time—Azimuth frequency domain. The main steps of the RDA in its basic version are:

1. **Range Compression**: the range matched filter, defined as the complex conjugate of the FFTed pulse replica, is applied to each pulse.
2. **Range Cell Migration Correction (RCMC)**: the relative motion between the antenna and the targets causes their migration through several range pixels. This effect can be corrected through a range interpolation or by applying a convenient phase multiplier.
3. **Azimuth Compression**: the azimuth matched filter can be defined directly in frequency domain and applied to each azimuth line.

AI-based SAR image formation

The main drawback of state-of-the-art algorithms is the enormous computational cost required.

The developed algorithm architecture is based on a two-step approach:

1. Traditional algorithm for range compression
2. DL model for azimuth compression

The reason for starting with the range compressed product is that pulse compression is a simple operation that can be applied to a raw product by exploiting a filter always equal to itself, which can be defined a priori by knowing the characteristics of the transmitted signal. Moreover, the real trick of SAR image formation, which coincides with the most demanding computational burden, is represented by the following operations in the Range Doppler domain. Thus, this preliminary prototype, shown in Figure 1, is a hybrid version of traditional operation and data driven-based approach.

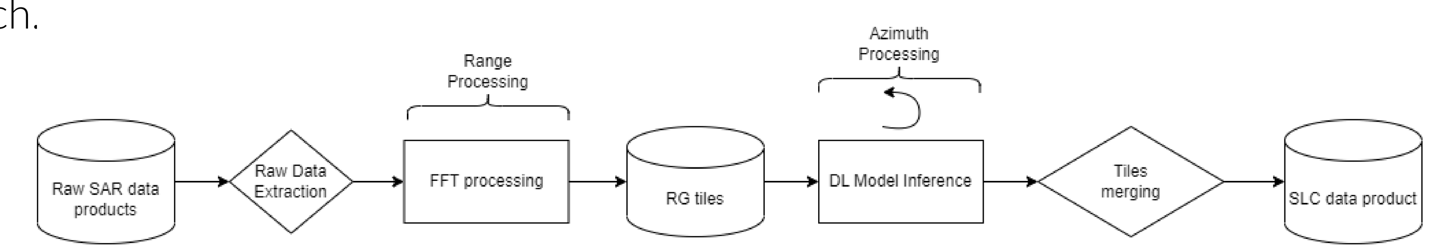

Figure 1. SAR focusing algorithm architecture.

To train the SAR focusing algorithm, a dataset comprised of Sentinel-1 (S1) Interferometric Wide (IW) products have been generated, which can be freely download through the Copernicus Open Access Hub [2]. A total of 52 S1 products have been processed to generate a dataset with range compressed and Single-Look Complex products. A Convolutional Neural Network (CNN) is trained on the generated dataset, obtaining the following results in terms of accuracy (with a tolerance of 0.5 on pixel values) and Structural Similarity Index Measure (SSIM):

Table 1. SAR focusing results with DL model.

	Train	Val	Test
Accuracy	85.10 + 14.23%	81.20 + 15.08%	81.51 + 13.76%
SSIM	0.449 + 0.150	0.402 + 0.160	0.390 + 0.141

Figure 2 shows an example of an inference performed on an entire IW swath (left) and on a single IW burst (right).

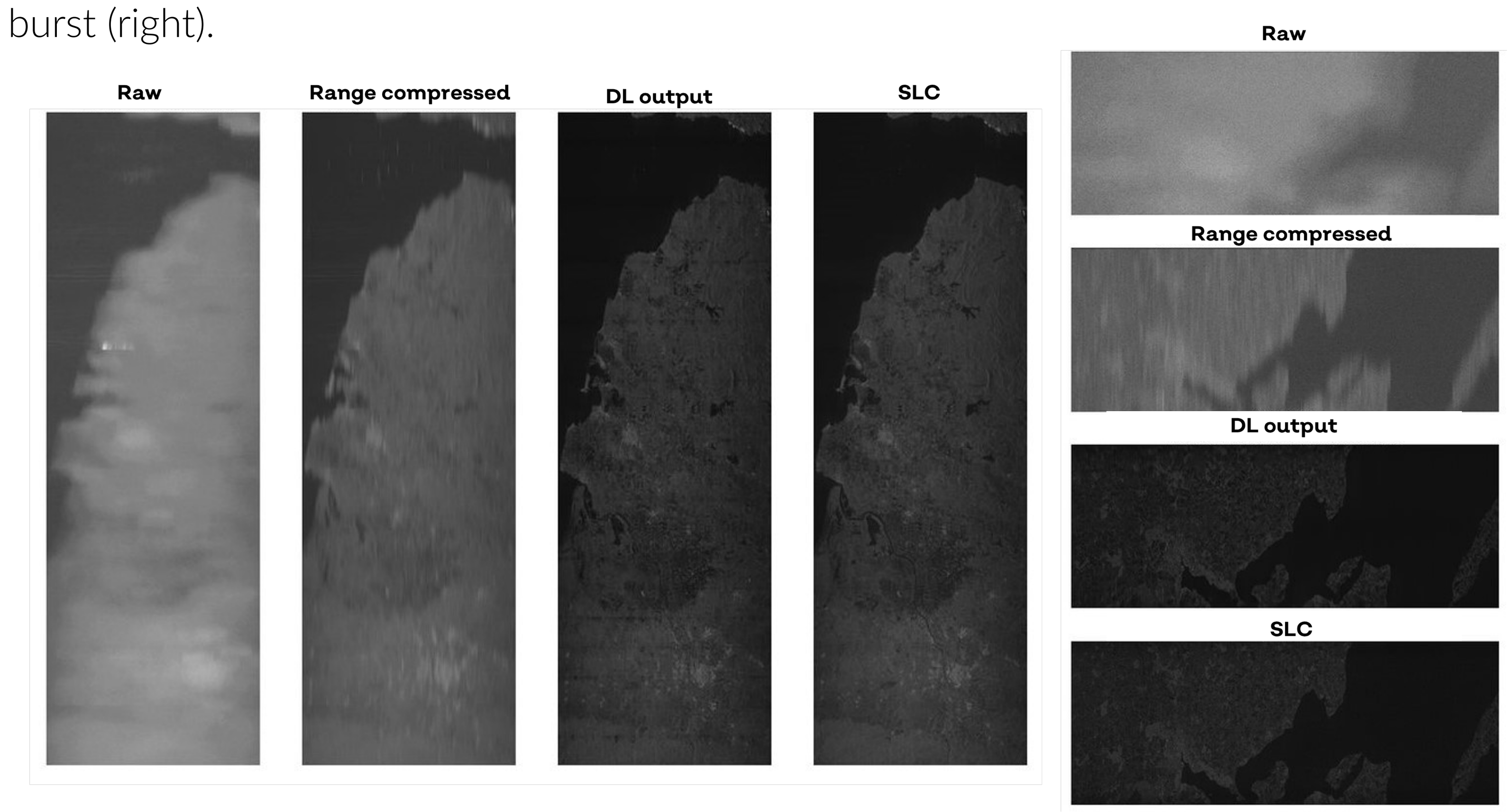

Figure 2. SAR focusing result.

Onboard ship detection

A DL ship detector network based on the state-of-the-art YOLO model has been trained for the ship detection task. The model has been preliminary trained on the LS-SDD-v1.0 dataset [3] and then fine-tuned on a custom dataset generated by manually labeling a subset of S1 IW products.

To evaluate its performance, the model has been tested on data focused with RDA and our AI-based approach. Table 2 reports the overall results obtained.

Table 2. Ship detection performance.

Focusing type	Precision	Recall	F1-score
RDA	0.717	0.966	0.810
AI-based	0.789	0.685	0.704

Figure 3 shows an example of the ship detector outputs:

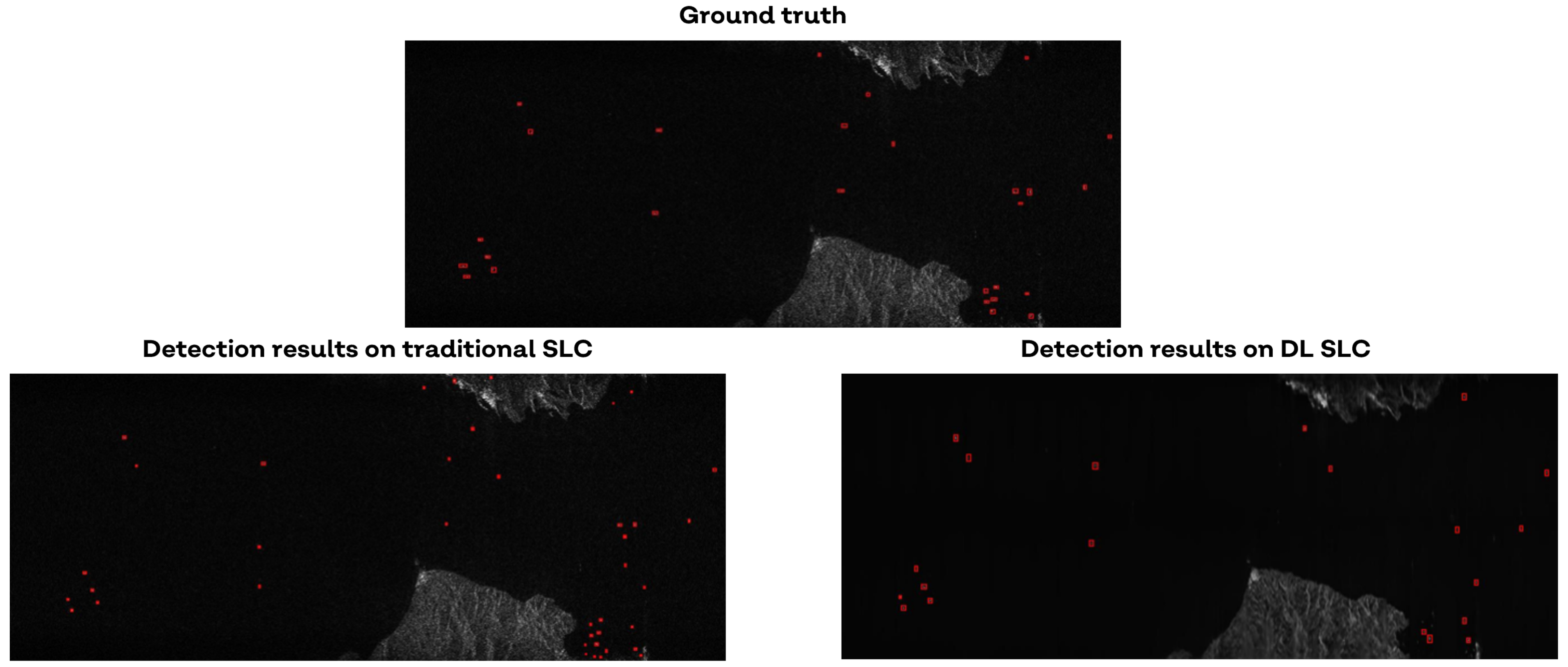

Figure 3. Ship detection example.

Deployment

The developed pipeline has been optimized and tested on two embedded devices (NVIDIA Jetson Nano and NVIDIA Jetson Xavier) to demonstrate the potential feasibility of running it onboard. Table 3 summarizes the overall results in terms of inference time.

Table 3. Deployment results for a single burst [sec].

Processing step	NVIDIA Jetson Nano	NVIDIA Jetson Xavier
Range compression	3.09	1.41
Azimuth compression	16.54	9.21
Ship detection	1.23	0.53
Total	20.86	11.15

References

[1] Ian Cumming and Frank Wong. *Digital Processing of Synthetic Aperture Radar Data*. 2005.

[2] European Commission ESA. Copernicus open access hub, 2023. URL `https://scihub.copernicus.eu/`.

[3] Zhang et al. Ls-ssdd-v1.0: A deep learning dataset dedicated to small ship detection from large-scale sentinel-1 sar images. *Remote Sensing*, 12(18), 2020. ISSN 2072-4292. doi:10.3390/rs12182997. URL `https://www.mdpi.com/2072-4292/12/18/2997`.

[4] Xiao Xiang Zhu, Sina Montazeri, Mohsin Ali, Yuansheng Hua, Yuanyuan Wang, Lichao Mou, Yilei Shi, Feng Xu, and Richard Bamler. Deep learning meets sar: Concepts, models, pitfalls, and perspectives. *IEEE Geoscience and Remote Sensing Magazine*, 9(4):143–172, 2021.