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APPLYING DEEP LEARNING TO P-BAND SAR TOMOGRAPHIC IMAGING IN PREPARATION FOR THE FUTURE BIOMASS MISSION

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ABSTRACT

With Synthetic Aperture Radar tomography, it is possible to reconstruct reflectivity profiles in the direction orthogonal to the line-of-sight. When only a small number of interferometric baselines is available, the spatial resolution of profiles produced by beamforming is insufficient. While many iterative algorithms have been proposed in the past years to achieve improved tomographic reconstructions, these methods often require a large computational cost. In this paper we explore the use of a light-weight neural network to dramatically accelerate tomographic reconstruction in anticipation of the deluge of data generated by the future BIOMASS satellite.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) tomography is a technique that allows the creation of 3D images of urban or forest scenes using a set of coherent, co-registered 2D SAR images. The goal of this process is to reconstruct reflectivity profiles for each 2D location in the direction orthogonal to the radar line-of-sight. The future ESA BIOMASS mission will use P-band SAR technology and retrieval methods, including SAR tomography, to produce precise biomass maps of tropical, temperate, and boreal forests, along with height information and disturbance patterns, to understand the global carbon cycle [1]. In contrast to tomographic reconstruction in urban environments where the individual complex amplitude of each scatterer is estimated, in high vegetation only a real-valued reflectivity profile can be recovered. Such a profile is typically modeled using continuous functions [2], which prevents the application of methods adapted to sparse data, such as MUSIC, to reconstruct it from tomographic data. In the literature, non-parametric spectral estimation techniques, such as *beamforming*, i.e. the discrete Fourier transform, and

Capon's filter [3], or *Compressive Sensing (CS)*-inspired algorithms using a small number of parametric basis functions [4, 5] are applied to perform TomoSAR focusing on forests. While the EM wave propagation model is approximately linear, and the first methods are based on the application of filters which are also linear, a non-linear processing can lead to super-resolution, as with regularized wavelet approaches for example [4].

The BIOMASS mission will cover more ground than any previous airborne mission, providing many large-scale images, albeit with poorer slant-range resolution. As *beamforming* and *Capon* lead to a reconstruction with coarse resolution (in addition to suffering from very strong sidelobes for the former), the correct estimation of reflectivity profiles using these methods will be difficult. *CS*-based algorithms produce higher-resolution results, but are generally iterative and require a large computational effort, which limits their applicability to the huge amounts of data produced by the BIOMASS mission. The application of deep learning methods, which are capable of producing high-resolution results while reducing computational time in many imaging domains, has so far been confined to height prediction in forested environments with SAR interferometry or tomography [6]. It therefore seems worthwhile to further develop methods in this field, with a view to applying them to future aerospace data.

This paper presents a computationally-efficient SAR tomographic inversion method on P-band airborne data using a nonlinear estimator in the form of a multilayer network, which paves the way for potential application to BIOMASS data. The proposed method is presented in more details in [7].

2. METHODOLOGY

The objective of our approach is to reconstruct tomographic profiles from P-band airborne data. A neural network (NN) is used to perform the reconstruction, since at test time simple feed-forward NNs are extremely fast.

To train the network, simulated data are generated using

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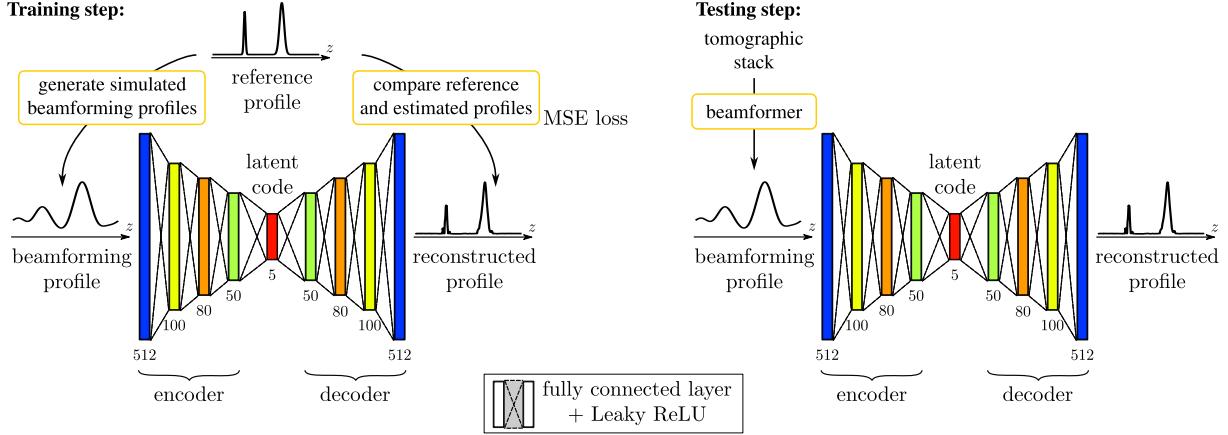


Fig. 1. Proposed neural network architecture: an auto-encoder is used to refine a beamforming profile and produce a sharper profile with reduced sidelobes. During training, reference profiles are generated, corresponding beamforming profiles are simulated and a supervised loss function is computed (mean squared error between the reference and reconstructed profiles). At test time, a beamformer produces a tomographic profile at each pixel. The network is then applied to each profile to produce a refined profile.

a model of forest reflectivity profiles to overcome the lack of labeled data. A mixture of 2 Gaussians over $N_z = 512$ uniformly distributed heights has been chosen here for its simplicity, following the model defined by:

$$p(z) = \frac{r}{\sqrt{2\pi}\sigma_1} e^{-\frac{(z-\mu_1)^2}{2\sigma_1^2}} + \frac{1-r}{\sqrt{2\pi}\sigma_2} e^{-\frac{(z-\mu_2)^2}{2\sigma_2^2}} \quad (1)$$

with the resulting 5 parameters uniformly sampled in the specified intervals: $\mu_1 \in [-10m, 10m]$, $\mu_2 \in [0m, 40m]$, $\sigma_1 \in [0.1m, 2m]$, $\sigma_2 \in [0.5m, 4m]$, $r \in [0, 1]$. Measurements and then *beamforming* profile are simulated from each of these reference profiles, to provide the latter as input to the network. An example of such a reference and corresponding *beamforming* profile can be seen in Figure 1.

We subsequently designed a network composed of 8 layers with leaky ReLU activation functions (Figure 1). We chose an encoder-decoder architecture with a bottleneck of low dimension (latent space of dimension 5) to limit the risk of over-fitting. The tomographic profile estimated by *beamforming* is provided as input and the network produces an improved estimation. A few thousand profiles are used at training with the Adam optimizer, a learning rate of 10^{-3} and a mean squared error loss between the simulated profile and the one estimated by the neural network.

In the testing phase, when the network is to be applied to real data for which the reference profiles are not known, *beamforming* profiles can be calculated from the measurements acquired and fed to the network to estimate the original profiles.

3. RESULTS

Figure 2 validates the efficiency of our method trained on simulated data and then applied to a real P-band tomogram from the TropiSAR campaign data acquired by the ONERA over the tropical forest of Paracou in French Guiana in 2009 [8]. The network was trained on profiles generated by a mixture of two Gaussians, one representing the ground and the other the tree crown. The reconstructed profile can be compared to the *beamforming* and *Capon* profiles obtained with a similar computation time during inference: the vertical resolution is clearly improved. The ground and canopy echoes are well separated in the profiles reconstructed by our deep neural network.

One of the greatest advantages of the proposed method is its rapidity. The Table 1 shows computation time comparisons between *beamforming*, *Capon*, the regularized inversion presented in [4] and our network, for a single TropiSAR tomogram or for the entire available tomographic stack at hand (6 images of size $1.3\text{km} \times 1.9\text{km}$). After training, the network presented has an inference time similar to that of *Capon*'s filter, and the training time itself becomes negligible when processing large amounts of data.

4. CONCLUSION

This paper presents a deep learning approach for tomographic inversion of P-band SAR tomographic measurements in the context of the forthcoming ESA BIOMASS mission [1]. It shows promising results on P-band airborne data, significantly reducing the computational time needed to reconstruct a large image compared to iterative techniques such as CS-based inversion. To apply this method to data from

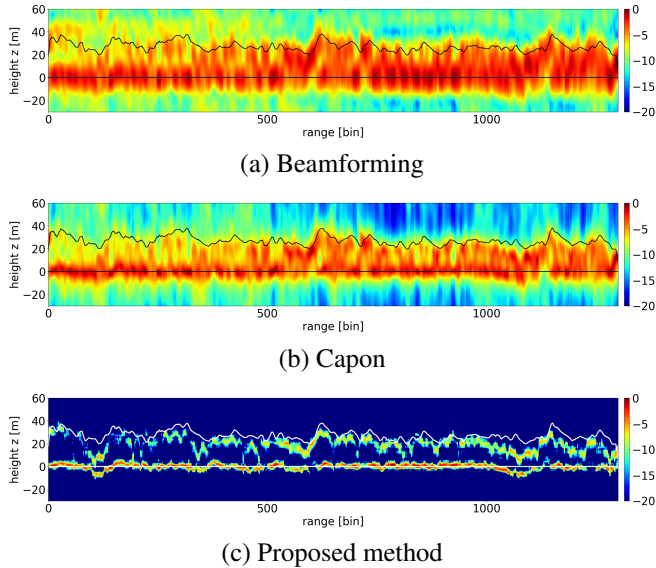


Fig. 2. Tomogram for a specific azimuth value in a tropical forest using P-band airborne data, reconstructed with the method: (a) Beamforming; (b) Capon; (c) Proposed neural network trained on simulated tropical forest profiles and applied to P-band airborne data. LiDAR data plotted over the tomogram help validate the obtained results.

Table 1. Order of magnitude of the computation time for the reconstruction of a single tomogram of size $1.3\text{km} \times 1.2\text{m}$ and the tomograms of the whole TropiSAR tomographic stack, on a cpu.

Method	Computation time (s)	
	Single	Stack
Beamforming	3	4 500
Capon	4	6 000
Reg. inv. [4] (CVX)	2 000	3 000 000
Proposed method	Training	200
	Inference	4

the BIOMASS satellite, adaptations will be necessary given the limited resolution of *beamforming* profiles. Airborne P-band images acquired during campaigns that prepared the BIOMASS mission [8, 9] may serve to produce both a high-resolution ground truth of the tomographic profiles and to simulate images at the coarse spatial resolution of the satellite.

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