M2 internship
Deep-Unrolling approaches for RADAR signal processing

1 Context and application

For many years now, deep learning has obviously enabled significant performance gains in multiple applications, even in fields that are not accustomed to using this type of method. Despite theses successes, deep learning-based methods still suffer from some drawbacks in applicative fields related to RADAR signal processing. First, these methods require a certain amount of annotated data to operate properly, especially when dealing with data that has high variability and a lot of noise (or equivalently low SNR as in RADAR). The other concern is that deep learning approaches are black boxes, making it very difficult to explain the results. On the other hand, traditional approaches do not require annotated data and are usually explainable from mathematical or statistical point of view. They are often expressed as solutions of an optimization problem arising from a data model. Rather than being learned from the data, the modeling is here handcrafted, which makes these techniques prone to loss of performance when a model mismatch occurs. In addition, some optimization algorithms take a long time to converge and require the tuning of several parameters.

An approach is to combine the best of both worlds is deep-unrolling [Gregor and LeCun, 2010, Solomon et al., 2020, Monga et al., 2021, Cai et al., 2021, Zhang and Ghanem, 2018, Brehier et al., 2024] (also reffered to as unfolding). This technique aims at constructing a neural network architecture in which each layer mimics an iteration of a model-based optimization algorithm. Training this network allows then for several benefits, notably an accelerated convergence (by achieving the same solution with a finite number of iteration/layers), and a better robustness to model mismatches. Last but not least, these architectures offer some explainability of the overall algorithm.

2 Objectives

The objective of this internship is to develop original deep-unfolding algorithms for the field of RADAR. More specifically, we propose to focus on two established problems: beamforming for large transmitters networks, and range-Doppler detection.

In the first problem (beamforming), the model-based approaches rely on compressive sensing methods [Gurbuz et al., 2008]. It will therefore be interesting to use unrolling algorithms on these approaches to improve the computational load [Gregor and LeCun, 2010]. Additionally, we will extend this work to integrate uncertainties related to the data model. This will allow us to adaptively correct uncertainties about the antenna, such as calibration problems, the presence of interference, missing data, etc. In this context, the annotated data can be generated using simulated data. We will also study the theoretical properties of these algorithms, particularly their convergence.

On a (possible) second part dedicated to detection, we will focus on range-Doppler data that suffers from a high level of clutter. Classically, the detectors are built from the inversion of an estimated sample covariance matrix. Unrolling the covariance matrix estimation can then be inspired by [Pouliquen et al., 2025], and adapted to structures that are relevant to RADAR applications (e.g. Toeplitz, Kronecker, block Toeplitz). Here too, the simulated data will be used for the training and validation.

3 Work plan

1. The student will study the main beamforming algorithms based on a constrained optimization problem. They will then construct a benchmark of these algorithms using simulated data, and selected real-world RADAR dataset.

2. By developping unrolled version of these algorithms, they will explore:

- the acelleration of the optimization scheme by leveraging existing works such as [Gregor and LeCun, 2010]. In this setup, unrolled algorithms will be trained to reproduce the results of classical algorithms with a constrained computational cost.
- We will then consider the integration of learnable parameters in order to model uncertainties in the data (e.g. a small perturbation of the dictionnary).
- They will also study the advantages of unrolling approaches compared to a traditional end-to-end neural networks. In particular, we expect these algorithms to require much less training data [Brehier et al., 2024].

3. The same methodological approach will then be applied to tackle range-Doppler detection applications. The second is more prospective, as the choice of algorithm to unroll, and covariance structure to adapt, remains a opened question.

The internship will be hosted at the SONDRA laboratory, a French-Singaporean research lab, and will be co-supervised by Chengfang Ren (CentraleSupélec), Jean-Philippe Ovarlez (ONERA), Guillaume Ginohlac (University of Savoie Mont Blanc), and Arnaud Breloy (CNAM). This internship could potentially lead to a fully funded PhD.

Duration: 4 to 6 months starting from February/March 2026.

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