# Deep Learning Computed Tomography

**Project Summary :**

This project aims at experimenting deep learning for reconstructing 3D volumes from series of radiographs (tomography). Main objectives are to reach an image reconstruction quality close to the results that can be obtained by costly iterative reconstruction methods ; while approaching a “reasonable” processing time (meaning that it could be used for routine applications).

**Detailed project :**

3D Computed Tomography (CT) techniques are widely used in the fields of medical and industrial imaging : 3D reconstruction of the inner parts of an acquired sample is obtained from series of projections (radiographs) measured around that sample. It is for instance the basic of medical X-Ray scanners.

The very first algorithm, denoted FBP (for Filtered Back-Projection), is a straightforward implementation of the inverse Radon transform. It recovers the 3D volume imaging the acquired sample from their projections. This direct reconstruction is massively used in routine applications because of its efficient computational cost. However, it is not adapted to complex acquisition geometry, suffers from noise and requires a large number of projections. As an alternative solution, iterative reconstructions (IR) are able to address these limitations but can not be used in routine applications because their computation time is up to 100 times the FBP’s one. This disadvantage becomes more and more relevant due to the very high improvements made on the acquisition devices. As an example, some X-Ray cameras now reach a resolution of few micrometers and the panel dimension is more than 5000 x 5000 pixels. With such a sensor panel, even with an iterative CT reconstruction, several hundreds of projections are mandatory for reconstructing a tomogram which will be sized 5000^3 voxels. Several approaches have been experimented to reduce the computation time such as multi-scale techniques. But even with such optimizations, a 5000^3-voxel tomogram reconstruction needs about 1 week to be reconstructed on a GPU-based implementation (on NVIDIA K80 CUDA device), whereas the acquisition time is about few minutes to 1h roughly, and FBP reconstruction would be about 2h.

The recent emergence of Deep-Learning makes the literature very sparse in the field of tomographic reconstruction. Moreover, the variety of investigations already made in the domain show that DL Tomography remains quite experimental. Last but not least, all the works realized until now are mainly conceptual (mathematical demonstrations and/or simulations) and/or address very specific problems of tomography (such as missing-wedge correction). No research and experimentation have been made until now to open DL Tomography to routine applications.

Knowing that the main characteristics of routine applications are: i) large size data to process, with a required result quality that only IR techniques can reach ; ii) “routine” means obviously that several datasets must be computed each day ; and, iii) “application” means that the kind of acquired samples remains roughly the same ; the main objectives of this project are : 1) how to reduce drastically the computation time thanks to DL in order to process several massive dataset per day while reaching a reconstructed image quality equivalent to the existing IR techniques ? ; 2) How to optimize the reconstruction by a DL approach knowing that, for a given application, the kind of samples remains more or less the same ; 3) More generally, what are the DL approaches, especially CNN model(s), that are generic enough so that they can address a wide range of tomographic applications as soon as an application-relevant training set composed of both acquisitions/reconstructions is provided to the CNN ?