Titre: Low Complexity Regularization of Inverse Problems: from
Sensitivity Analysis to Algorithms

Resume: Inverse problems and regularization theory is a central theme in
imaging sciences, statistics and machine learning. The goal is to reconstruct an
unknown vector from partial indirect, and possibly noisy, measurements of it. A
now standard method for recovering the unknown vector is to solve a convex optimization
problem that enforces some prior knowledge about its structure. This
talk delivers some results in the field where the regularization prior promotes
solutions conforming to some notion of simplicity/low-complexity.
These priors encompass as popular examples sparsity and group sparsity,
total variationand low-rank.

Our aim is to provide a unified treatment of all these regularizations
under a single umbrella, namely the theory of partial smoothness. This
framework is very general and accommodates all low-complexity
regularizers just mentioned, as well as many others. Partial smoothness turns out to be
the canonical way to encode low-dimensional models that can be linear spaces or more
general smooth manifolds. This review is intended to

serve as a one stop shop toward the understanding of the theoretical properties of the so-regularized solutions. It covers a large spectrum including: (i) recovery guarantees and stability to noise, both in terms of ℓ_2-stability and model (manifold) identification; (ii) sensitivity analysis to perturbations of the parameters involved (in particular the observations); (iii) convergence properties of forward-backward type proximal splitting, that is particularly well suited to solve the corresponding large-scale regularized optimization problem.