Abstracts

Geometric graph-based methods for high dimensional data

Presenting new methods for segmentation of large datasets with graph based structure. The method combines ideas from classical nonlinear PDE-based image segmentation with fast and accessible linear algebra methods for computing information about the spectrum of the graph Laplacian. The goal of the algorithms is to solve semi-supervised and unsupervised graph cut optimisation problems. The methods make parallels between geometric ideas in Euclidean space such as motion by mean curvature, ported to a graphical framework. These ideas can be made rigorous through total variation minimization, and gamma convergence results, and convergence of time stepping methods in numerical analysis. I will show diverse examples including image processing applications such as image and video labelling and hyperspectral video segmentation, and machine learning and community detection in social networks, including modularity optimisation posed as a graph total variation minimisation problem.

Model-based learning in imaging

One of the most successful approaches to solve inverse problems in imaging is to cast the problem as a variational model. The key to the success of the variational approach is to define the variational energy such that its minimiser reflects the structural properties of the imaging problem in terms of regularisation and data consistency. Variational models constitute mathematically rigorous inversion models with stability and approximation guarantees as well as a control on qualitative and physical properties of the solution. On the negative side, these methods are rigid in a sense that they can be adapted to data only to a certain extent. Hence researchers started to apply machine learning techniques to “learn” more expressible variational models. In this talk we discuss two approaches: bilevel optimisation (which we investigated over the last couple of years and which aims to find an optimal model by learning from a set of desirable training examples) and quotient minimisation (which we only recently proposed as a way to incorporate negative examples in regularisation learning). Depending on time, we will review the analysis of these approaches, their numerical treatment, and show applications to learning sparse transforms, regularisation learning, learning of noise models and of sampling patterns in MRI.

This talk will potentially include joint work with S. Arridge, M. Benning, L. Calatroni, C. Chung, J. C. De Los Reyes, M. Ehrhardt, G. Gilboa, J. Grah, A. Hauptmann, S. Lunz, G. Maierhofer, O. Oektem, F. Sherry, and T. Valkonen.