Dissertation topic

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Classification and monitoring of settlements using InSAR data

InSAR imaging systems provide very useful data for several remote sensing applications. Regarding urban land cover and land use systematic or emergency map actualizations, InSAR datasets might be indispensable in case the city is for most of the year covered by clouds. However, the higher resolution of new space-borne InSAR imaging systems, the complexity of urban areas and the geometrical distortions inherent to SARs require that the classification approach takes into account the spatial context of each pixel or image segment.

The most flexible and yet mathematically consistent way of modeling the probabilistic relations between the observed attributes and the possible classes of neighbouring image segments is through Probabilistic Graphical Models (PGMs). Among PGMs, Conditional Random Fields (CRF) is the most advantageous for image classification. The automatic learning of the CRF graph's structure and its parameters is known to produce models of better performance and potentially reveal unsuspected dependencies between the considered variables. Nevertheless, even the application of manually designed CRF models on remote sensing images very easily become computationally intractable, due to the potentially large image size and number of observed attributes.

From the application perspective, the goal of this PhD research is to use learned CRF models to accurately classify the Urban Structure Types (UST) of Munich (Germany) based on two InSAR datasets from the TerraSAR-X satellite obtained on ascending and descending pass directions. From the methodological perspective, this PhD focuses on the assembling and customization of a framework for learning the CRF graph's structure and its parameters in a tractable way. The learning framework involves: (1) parameter learning through the optimization of a convex objective function whose gradients are numerically computed based on approximate inference; (2) embedding the structure learning problem to the parameter learning problem, so that both can be learned by optimizing the same objective function; (3) application of an efficient user-defined heuristic for the gradual introduction of possible structure features in the optimization process.

Tasks 1 and 2 refer to the minimization of the L1-regularized maximum likelihood function having the Loopy Belief Propagation algorithm as the inference engine. Surprisingly, the L1-term pushes most of the parameters to zero, discarding in this way most features from the optimal CRF structure. Task 3 refers to the fact that in order to guarantee tractability, features have to be inserted gradually in the optimization process. As the L1-regularized maximum likelihood objective is a convex one, the feature insertion order does not affect the convergence of the algorithm, but it greatly affects the time it takes to converge, whereas inserting the most relevant features first will result in faster convergence. Instead of solely relying on any of the available costly measures for deciding which features to include next, a heuristic that guides the introduction of features in the optimization process is proposed. This heuristic firstly evaluates all features and inserts the best one(s). Then instead of evaluating all features again, only those semantically related to the best features are evaluated by any of the measures available in the literature. The feature semantic net is user-defined.

It is expected that accurate UST classifications from Munich can be generated using learned CRF models and InSAR datasets from different pass directions. We expect that the CRF models encode meaningful contextual relations between the observed and unobserved variables (i.e. image attributes and the segments classes, respectively). The discarded and selected structure features will point out which and to what extent far and near range contextual relations between the observed and unobserved variables are pertinent. The optimized CRF models will also express how important is a second InSAR dataset from an opposite pass direction to the accuracy of the UST classification.