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Predicting building façade structures with multilinear Gaussian graphical models based on few observations

Sandra Loch-Dehbi *, Lutz Plümer

Institute of Geodesy and Geoinformation, University of Bonn, Germany

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ABSTRACT

This paper presents a new approach for the prediction of substructures in building façades based on sparse observations. We automatically generate a small number of most likely hypotheses and provide probabilities for each of them. Probability density functions of model parameters which in most cases are non Gaussian and multimodal are learned from training data and approximated by Gaussian mixtures. Relations between model parameters are represented by non-linear constraints. For stochastic reasoning we design and apply a special kind of Bayesian networks which involves both discrete as well as continuous variables, a scenario which often suggests the use of approximate inference which however is infeasible in the face of a huge number of competing model hypotheses. In order to be able to scan huge model spaces avoiding the pitfalls of approximate reasoning and to exploit the potential of both observations and models, we combined Bayesian networks with constraint logic programs. We designed a method which breaks down the problem into a feasible number of subproblems for which exact inference can be applied. We illustrate our approach with building façades and demonstrate that particularly for buildings with strong symmetries number and position of windows can be deduced on the basis of ground plans alone.

1. Motivation and context

Nowadays 3D building models are widely available but they mostly do not contain detailed structure and semantical information. Facades where details are only provided by texture mappings are often not sufficient for many applications. Semantics that can be encoded by the standardized data model CityGML (Gröger, Kolbe, Czerwinski, & Nagel, 2008) are important for many scenarios such as rescue scenarios or the calculation of energy balances. Detailed information about doors or windows in an apriori unknown building might be crucial for rescue teams to accelerate assistance.

Haala and Kada (2010) emphasize the importance of detailed building reconstruction and give an overview of approaches in the context of automatic city modeling. However, building models that represent building parts such as windows or doors explicitly are rare and up to now modeled manually or semi-automatically in most cases. Moreover, an automatic reconstruction in general relies on high-resolution measurements such as 3D point clouds from laser scans or features extracted from images. This requirement is often not able to be satisfied in an appropriate way so that we have to cope with an apriori small number of observations instead. While ground plans are already available by the use of data sources such as official data or Open Street Map the acquisition of 3D point clouds is far costlier.

As a consequence, our central motivation is to predict unknown substructures in buildings based only on few observations. While most approaches expect observations of adequate density, characteristic for our approach is that we are able to generate best hypotheses for a building model based on otherwise insufficient measurements, in particular ground plans. Additional data may lead to a verification or falsification of models which however is less expensive than reconstructing a building bottom-up from measurements. Fig. 1 illustrates our approach for predicting a row of windows in a complex façade of the Poppelsdorf Castle in Bonn, Germany (see Fig. 1a). The hypothesis about the windows in Fig. 1c is the result of the reasoning process that incorporated the ground plan of the building (red line) as well as measurements of single embrasures (dotted lines in Fig. 1b). Full observations of all windows are not necessary to generate a hypothesis of this quality. The width of façades is for example correlated to the number of windows, the width of windows and the distance between windows and together

* Corresponding author.
E-mail addresses: loch-dehbi@igg.uni-bonn.de (S. Loch-Dehbi), pluemer@igg.uni-bonn.de (L. Plümer).
URL: http://www.ikg.uni-bonn.de.

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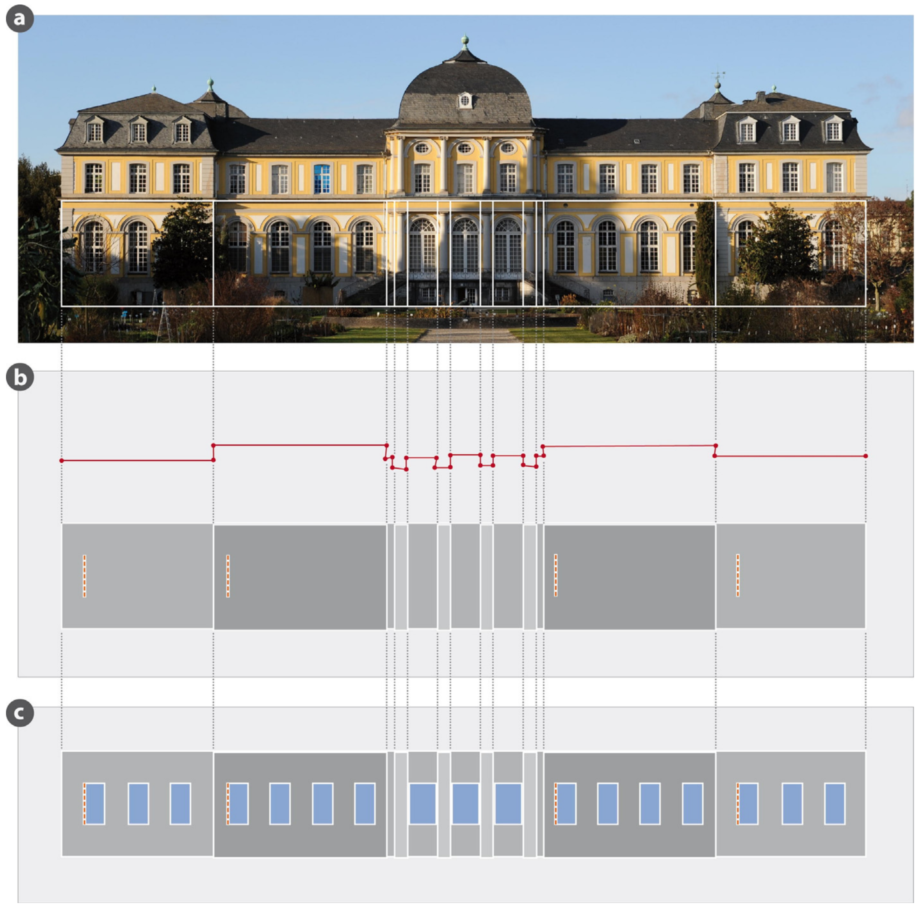

Fig. 1. Reasoning process for predicting a complex façade: (a) reference image: façade of Poppelsdorf Castle, (b) input: ground plan (solid line) and measurements of embrasures (dotted lines) as observations, and (c) output: resulting hypothesis.

with a model for these building parameters, especially probability distributions, the space of hypotheses becomes strongly constrained. The use of Gaussian mixture models, constraint solvers and stochastic models help to cope with the apriori infinite space of a hybrid building model.

Generating good hypotheses becomes possible due to the regularities that can be found in buildings. Poppelsdorf castle as illustrated in Fig. 1 is an example of a cultural heritage buildings which are characterized by symmetries and parallel or orthogonal structures. What is obvious and especially pronounced in façades of cultural heritage can be observed as well in modern buildings. Model parameters such as width of windows or height of floors follow certain architectural restrictions. In turn, the number of windows that can be placed within one floor is restricted by the width of the façade. A typical constraint characterizing this relation has the form $w_f = d_l + d_r + n_w * w_w + (n-1) * d_w$ where w_f denotes the width of the façade, d_l and d_r the distances to the left respectively right side of the façade, w_w the width of the windows and d_w the distance between windows and n_w the number of windows. Thus we get a bilinear formula with continuous parameters (w_f,d_l,d_r, w_w,d_w) and one discrete parameter (n_w) and products formed from a continuous and discrete factor. Beyond that, the values of the model parameters have characteristic distributions that can be learned from examples. Fig. 2 illustrates these distributions. Note that none of these distributions is Gaussian. Instead, both are multi-modal. We used a kernel density estimation (Bowman & Azzalini, 1997) that can, however, be approximated rather neatly by Gaussian mixtures with few components and small variances. It will turn out that this is an essential prerequisite for the possibility of using efficient inference algorithms. All in all, this prior knowledge together with a powerful reasoning algorithm allows to generate good hypotheses of buildings.

To generate the best hypotheses we make use of Bayesian networks as a special kind of probabilistic graphical models. Bayesian networks are the directed variant of graphical models and have been established to be powerful tools for reasoning with uncertain data. The domain model for buildings can be represented as a hybrid Bayesian model with discrete as well as continuous parameters. It is further characterized by multilinear equations with apriori unknown discrete variables and mixtures of Gaussians that make inference unfeasible. While there exist efficient inference algorithms for discrete networks, inference in hybrid networks remains to be a challenging task. Koller and Friedman (2009) pointed out that the resulting number of mixture components is exponential in the number of unassigned discrete variables in the worst case. Lauritzen and Jensen (2001) developed an efficient algorithm which is able to tackle the problem of exact inference in restricted hybrid networks. It provides a solution whose distributions are correct for discrete variables. For continuous variables first and second moments of the posterior distribution are correct while the true distribution might be a Gaussian mixture. It is sufficient for many applications since it is often the discrete variables that are queried or the resulting Gaussian distribution is close to the original Gaussian mixture. In contrast, the joint distributions of the continuous model parameters for façade prediction are multimodal and so are the marginal distributions. As a consequence, an approximate inference algorithm as proposed by Lauritzen and Jensen (2001) would prevent the computation