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Building reconstruction by extraction of object-specific corners and their aggregation

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Abstract: This paper presents a procedure for automatic building extraction from multiple overlapping images by stepwise integrating knowledge of a hierarchical building model. The reconstruction comprises the extraction of the geometric as well as the semantic object description, i. e. the interpretation of the objects. Due to the close interaction between reconstruction and interpretation the maximum of available knowledge can be exploited during all steps of the reconstruction process and facilitates and stabilizes the reconstruction.

1 Motivation

During the last years, three-dimensional building data have increasingly gained importance for practical applications as in architecture and planning. Aerial images give a suitable data base for reconstructing buildings using photogrammetric techniques. To reduce the cost of time-consuming manual data acquisition, in recent years automatic 3d building reconstruction became an active research area. In the literature essentially two main strategies are proposed: These are a.) data-driven driven approaches which start with the geometric reconstruction of line or polygon features followed by model based grouping and interpretation. b.) model-driven approaches which lead to building instances by model to image matching.
Both approaches are characterized by competing features which are given by the employed model. Using model-driven techniques the exploitation of a strong model is possible with the disadvantage that predefining all possible building types is required. Using data-driven techniques a generic building model like a polyhedral model can be employed. It enables the reconstruction of a wide range of buildings but does not provide such strong building specific constraints and therefore needs for a strong data-driven feature reconstruction.
To benefit from both approaches this paper proposes to use a hierarchically structured building model to perform the object extraction by a close integration between geometric reconstruction and interpretation and thus enables to exploit building knowledge step by step in a hierarchical reconstruction procedure. The automatic reconstruction is based on building-specific components derived by multi-image correspondence analysis and their hierarchical aggregation.

2 Building Model

The modeling of knowledge about the scene by means of object-, image- and sensor-modeling plays an important role in automatic object extraction from image data. To

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cope with the wide variability of the objects and the complexity of their appearance in the images we propose a coherent hierarchical building model in 2d as well as in 3d. The component-based building hierarchy compounds a part-of hierarchy which comprises different levels of domain-specific aggregation and a specialization hierarchy which distincts different object specializations within each aggregation level. It is further specified in earlier papers (e. g. cf. FISCHER et al. 1998).
The proposed building model enables the access to the semantics of building components by using the class-specific geometric and topologic properties of the object components as well as connectivity relations between components of different levels. On the one hand this enables to build up generic building structures step by step, on the other hand the incompleteness of the initially derived symbolic image description can be handled by starting with local analysis and sucessively integrating more specific building constraints.

3 Reconstruction Strategy

One decisive subtask in the complete hierarchical reconstruction process is the transition from 2d image space to 3d object space, that is to derive 3d object parts which serve as an appropriate basis for the subsequent aggregation process. For the transition into object space we use building components of type `corner` which are described by feature aggregates in 2d as well as in 3d (cf. fig. 1). The choice of using corners for the transition into 3d is motivated by the following reasons:
Observability: The projections of corners into the images are image structures which show a high stability against noise and occlusion.
Structure: In contrast to single feature characteristics, the topological and structural properties of corners are more suitable for control and evaluation during the correspondence analysis.
Interpretation: The richness of the observable geometry and topology of the corners, especially in 3d object space, is suitable for interpreting the observed 3d descriptions. The interpretation then can be used for stabilization and verification purposes.
Aggregation: The corner geometry as well as the corner semantics give powerful information for the subsequent 3d aggregation process (cf. section 6) and thus enables to use a generic model for 3d aggregation.
The corner reconstruction process follows the hypothesize and verify paradigm. Hypotheses are built up mainly data-driven inferring the class membership of the observed data to a corner class from analyzing the observable geometric description. Corner hypotheses represent model instances with fixed geometry, topology and structure. Having

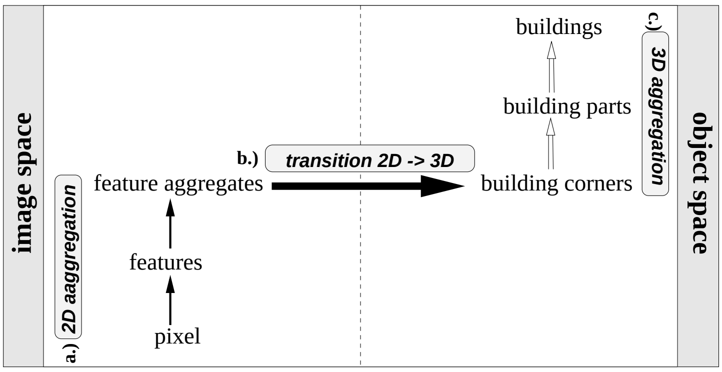

Fig. 1: shows the proposed strategy for building reconstruction. It comprises 3 steps **a.** 2d aggregation from pixel to feature aggregates, **b.** 3d reconstruction and interpretation for the transition from feature aggregates to corners **c.** 3d aggregation of corners to buildings.

built up the hypotheses, the verification can be performed model-driven exploiting the class-specific constraints for evaluation and for increasing the accuracy of the reconstruction. Thus a close interaction between geometric, topologic and semantic reconstruction is performed.
The corner reconstruction is formulated as a multi-image procedure using all available image data simultaneously. The interior and exterior image orientation is presumed to be known and is used for geometrically restricting the search during the correspondence analysis.

4 3d and 2d Corner Model

For the transition into object space we use building components of type `corner` which are described by feature aggregates. They represent components of a general polyhedron which additionally are specified by building-specific geometrical, topological and structural properties given by constraints in 2d as well as in 3d.
Each corner $\mathtt{C} = (\mathtt{V}, \psi_{\mathtt{C}})$ of order n is described by the vertex $\mathtt{V}$ composed from the corner point $\mathtt{P}$ and each n lines L and regions R that are preliminarily open-ended in their spatial extension (cf. fig. 2 a.) and thus represent plug elements for grouping and aggregating corners. The graph representation (cf. fig. 2 b.) expresses the topologic and structural description of a corner where the graph nodes represent features and the graph arcs the adjacency relations between them. The building-specific part of the corner model, which makes the difference of a building corner from a general polyhedral corner depends on the corner specialization hierarchy, which divides corners into subclasses $\psi_{\mathtt{C}}$.

3d Corner Model: The corner specialization in 3d depends as well on the corner topology and its geometry. Therefore we use a *two-level specialization hierarchy.* Each subclass implies class dependent constraints $\Theta_{\psi_{\mathtt{C}}}$ onto the form description, the vertex $\mathtt{V}$. On the first level of the specialization hierarchy we use unary constraints which refer to single components of a corner. They especially restrict the corner components of type line to building-specific qualitative attributes like being horizontal, vertical or sloped. On the second level of the specialization hierarchy we use binary constraints which refer to the geometric relationship of pairs of corner components and likewise restrict the corner components of type region to building-specific attributes like being horizontal or vertical. Examples of corner classes are shown in fig. 4.
If no constraints are attached to the corner we call it the unconstrained corner with class label $\psi_{\emptyset}$, which is identical to a polyhedral corner, that is a vertex $\mathtt{V}$.

2d Corner Model The image model aims at describing object components coherent to the 3d modeling to provide direct access from image observations to 3d objects and vice versa. The image representation coherently uses features of type points, lines and regions which can be derived by an appropriate feature extraction. We use the procedure proposed in Fuchs 1998 for deriving a polymorphic symbolic image including the mutual neighborhood relations between features which are stored in a feature adjacency graph analogous to the graph representation in object space (cf. fig. 2 b.).
As the geometric variability of the appearance of the different corner types in the images, due to the image characteristics and the characteristics of the feature extraction procedure is too large for an efficient representation in the image model, we renounce on

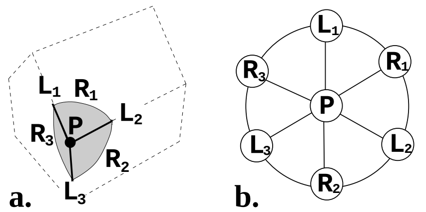

Fig. 2: a. shows a corner represented by its components points, lines and regions. b. shows the graph representation of a corners.

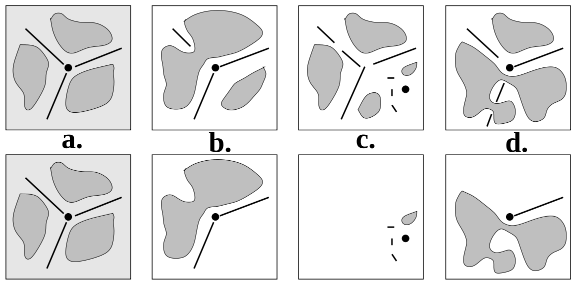

Fig. 3: shows some typical deviations of the observed vertex features (first row) and features with a neighborhood relation to the corner point (second row). a. shows the ideal projection of a corner of order 3, b.-d. show possible appearances of extracted image corners differing from the ideal projection.

integrating the corner specialization into the image model. Thus the 2d corner model is a vertex model described by the topological and structural properties of the appearance of a corner in the images depending on its underlying vertex. To take into account the uncertainties of the feature aggregates (cf. fig. 3) we formulate the image model by a vertex classification model (cf. FISCHER et al. 1998) which classifies feature aggregates being vertices or non-vertices taking for reference the ideal projection of a corner of order 3 (cf. fig. 3 a.).

5 3d Corner Reconstruction

Generation of 3d Corner Hypotheses: The corner reconstruction starts with the generation of corner hypotheses and comprises the reconstruction of 3d vertices and their interpretation as 3d corners.

Initial form reconstruction of 3d vertices: By multi-image correspondence analysis we build an initial reconstruction of 3d vertices V^{3D}, which possess the topological and structural properties of corners as defined by the image model.

We start with selecting vertices V^{2D} by point-induced 2d aggregation analyzing the extracted points, lines and regions and their mutual neighborhood relations. The selected vertices serve as a base for the correspondence analysis which is formulated as search procedure extending over three layers. In the first layer it starts with selecting the most promising vertex $\mathtt{V}_i^{\mathrm{2D}}$ in image i using a priority list of the 2d vertices which is built up by vertex classification based on the image model considering stability, uniqueness and structural richness of the vertices. The second layer establishes a stereo correspondence of vertices $[\mathtt{V}_i^{\mathrm{2D}}, \mathtt{V}_j^{\mathrm{2D}}]$ in the images i and j. It evaluates the structural similarity of matching candidates considering the epipolar constraint. The third layer generates a multi-image correspondence tuple $[\mathtt{V}_i^{\mathrm{2D}}]$. Epipolar geometry once again gives restrictions of the search space.

Based on the correspondence tuple $[\mathtt{V}_i^{\mathrm{2D}}]$, the transition to object space is performed by a joint forward intersection of the corresponding vertex components points and lines using all images simultaneously. Epipolar geometry once again facilitates the matching task.

Interpretation: Next the vertex interpretation can be performed by assigning each 3d

vertex to one or several alternative corner classes defined by the 3d corner specialization hierarchy. This step is performed in object space as the 3d information defines stronger restrictions than are available in 2d.
We hierarchically check possible class-specific constraints in two stages: We start checking unary constraints on the first level of the corner specialization hierarchy. We use qualitative line attributes that depend on their slope with respect to the corner point, given by the qualitative geometric labels `horizontal (h)`, `vertical+ (v+)`, `vertical- (v-)`, `oblique+ (o+)` and `oblique-(o-)`. Depending on the identified unary constraints possible binary constraints are checked. Examples of binary constraints are `symmetry` of two lines with respect to the vertical or `orthogonality` of two lines. The explicit definition of subclasses on this level is not sensible as we cannot predefine it without restricting the variability of the corners. Thus, a set of rules relates the identified constraints of each vertex to a class label $\psi_{\mathtt{C}}$.
Because in general the vertex observations may be incomplete we further use the corner model for prediction by inferring complete model instances from the observations. We predict corner components which are unobservable due to disturbed features or feature adjacency relations and predict class-specific constraints.
The interpretation result are one or several corner hypotheses $\mathtt{C}^{3D} = (\mathtt{V}^{3D}, \psi_{\mathtt{C}})$ for each vertex $\mathtt{V}^{3D}$. If no constraints are attached to the corner we call it an unconstrained corner with the class label $\psi_{\emptyset}$.

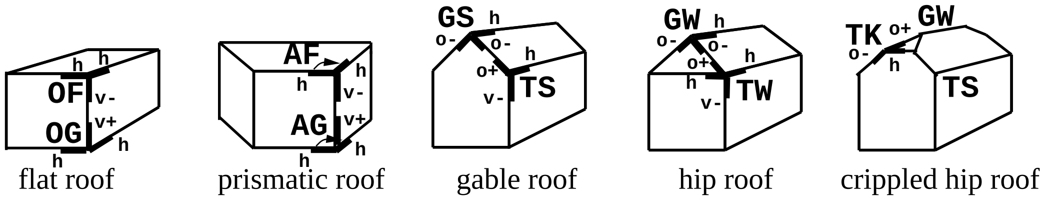

Fig. 4: Different corner types that are defined by the building specific corner specialization hierarchy.

Verification of 3d Corners: The derived 3d corner hypotheses have to be verified for two reasons. 1. Each 3d vertex may lead to alternative 3d corners. This ambiguity has to resolved. 2. The predicted corners have to be sustained by additional observations to avoid blind prediction.
In contrast to the mainly data-driven generation of corner hypotheses the verification is performed model-driven and profits from the strong knowledge of the model instances as follows: a.) The geometric model instances give approximate values for further steps of the analysis and b.) the class membership defines class-specific constraints that can be used for geometric stabilization and for checking the conformity of data and model.
The verification of the corner hypotheses is performed by statistical analysis and is formulated as an optimization problem for finding the best interpretation $\hat{\mathtt{C}}$ of the data $[\mathtt{V}_i^{2D}]$ from all possible corner hypotheses. Using Bayes theorem, the optimization of the conditional probabilities $P(\mathtt{C} \mid [\mathtt{V}_i^{2D}])$ can be broken down to optimizing the data-dependent part $P([\mathtt{V}_i^{2D}] \mid \mathtt{C})$ which evaluates how good the corner instance fits the observed image features of the vertex correspondence tuple $[\mathtt{V}_i^{2D}]$ and optimizing the model-dependent part $P(\mathtt{C})$ which gives information on the probability distribution of the different corner classes.
Using the classical techniques for modeling observation errors the data-dependent optimization part can be derived from the residuals $\hat{\boldsymbol{e}} = \boldsymbol{y} - \hat{\boldsymbol{y}}$ of the optimal estimation

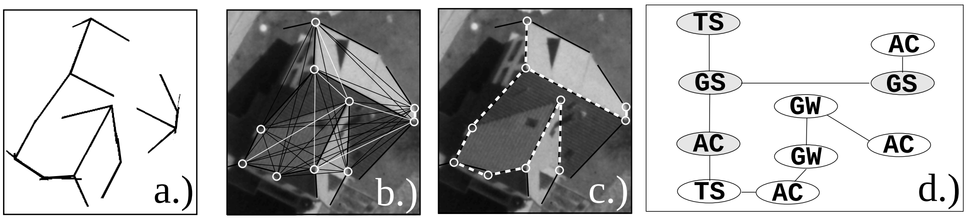

Fig. 5: shows the reconstructed corners and the corner grouping. a.) wire frame representation of the reconstructed corners. b.) corner connections of class compatible corners denoted in black. c.) adjacency relations of the corners, which fulfill the class-compatibility as well as the compatibility of the geometry. d.) representation of the corner adjacency graph CAG (node attributes cf fig. 4).

$\hat{\boldsymbol{y}} = f(\hat{\boldsymbol{\beta}})$ of the corner parameters $\boldsymbol{\beta}$ and depends on the squared sum of the residuals $\Omega = \hat{\boldsymbol{e}}^T \boldsymbol{\Sigma}_{yy}^{-1} \hat{\boldsymbol{e}}$ with $\boldsymbol{\Sigma}_{yy}$ being the covariance matrix of the observations $\boldsymbol{y}$. Each corner $\mathtt{C}$ of order n in principle requires $3 + 2 \cdot n$ geometric parameters $\boldsymbol{\beta}$ which are reduced by the class specific constraints. The estimation uses multi-image point and line observations simultaneously. A refined selection of supporting observations $\boldsymbol{y}$ is performed by back-projecting the corner hypothesis into the images to get access to features which were originally not contained in the selected vertices due to incompleteness, fragmentation and missing neighborhood relations of the extracted image features.
The model-dependent optimization part depends on the a priori probability $P(\mathtt{C})$ for the corner class $\psi_{\mathtt{C}}$ and can in principle be obtained empirically by learning. At present we prefer specialized corners $\psi_{\mathtt{C}}$ before unconstrained corners $\psi_{\emptyset}$ and assume equally distributed corner classes $\psi_{\mathtt{C}}$.

6 3d Corner Grouping and Aggregation

The next step in the reconstruction is to perform the 3d grouping and 3d aggregation of corners to result in a complete object description.

Grouping of 3d Corners: In contrast to the subsequent 3d aggregation, the grouping connects the corners solely using the knowledge of the aggregation level of corners.
The grouping is performed in two steps: The first step is to check the *qualitative compatibility* of corner pairs which depends on the qualitative geometric connectability of the corners that is fulfilled by compatibility of the class specific constraints of the corners given by its class. To test the qualitative compatibility a class-connection-table is used that contains the class compatibility of the corners and their components.
The class-compatibility of corners is necessary but not sufficient for the grouping of corners because the corner instances can be geometrically incompatible. Therefore, the second step in grouping is to check the *quantitative compatibility* of the class-compatible corner pairs analysing the underlying geometric corner instances. E. g. for connecting two lines they have to be collinear, two regions have to be coplanar. The geometry can be statistically tested (cf. HEUEL et al. 2000) exploiting the statistical properties of the corner components given by the covariance matrix of the estimated feature geometry which results from the parameter estimation during the corner reconstruction.
The result of the grouping process is a corner adjacency graph CAG (cf. fig. 5 d.)), whereas the graph nodes are 3d corners and the graph arcs denote a connection between corners, possibly attributed by their connection probability.

Aggregation of 3d Corners: The 3d aggregation of components leads to objects of a higher level of the building hierarchy. For indexing in higher level building components the building-specific aggregation relations given by the structural decomposition of the objects into components are used. For the transition between different levels of the aggregation hierarchy we use analogously to the corner reconstruction a parametrization for describing the geometry and topology of the object (cf. fig. 6 a.)) and a graph representation for describing the structural composition of the objects (cf. fig. 6 b.)). The corner adjacency graph is used to facilitate and focus the 3d aggregation e. g. using subgraphs for indexing into parameterized building primitives or building parts (cf. FISCHER et al. 1998). The attributation of the graph nodes given by the corner classification enables the access to the building type and its parameters in the parametrized representation. The corner geometry is used for deriving the parameter instances of the parametrized objects. E. g. the length of a gabled roof building can be determined using the corner pairs `(GS,GS)`,`(TS,TS)` or `(OG,OG)` in fig. 6. One example for corner aggregation is shown in fig. 7.

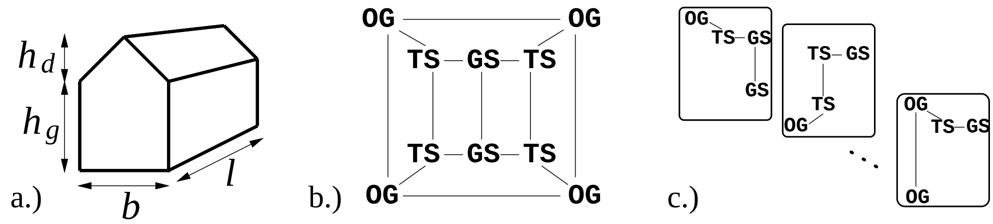

Fig. 6: shows different representations of a gable roof building a.) the parameter representation, b.) the graph representation c.) different subgraphs, which are sufficient for the complete parameter instantiation during the 3d corner aggregation.

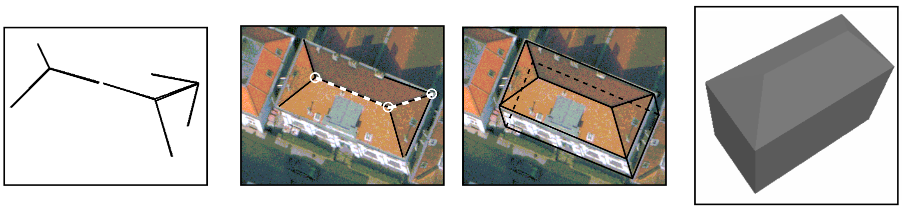

Fig. 7: shows an example for grouping and aggregation of reconstructed corners to hip roof building.

7 Results and Conclusions

The presented procedure for building reconstruction and interpretation is tested with stereo image data with $2-9$ overlapping images using image scales between $1:4000$ up to $1:12000$ and $10cm - 24cm$ pixel size on ground and shows promising results, especially in suburban areas. For details we refer to LANG 1999.

Fig. 8 shows the result on the data set *Avenches residential* with scale $1:5000$ which was internationally distributed for the Ascona workshop '95 on *Automatic Extraction of Man-Made Objects from Aerial and Space Imagery*. The corner reconstruction is performed using grey level images with $12cm$ pixel resolution. Altogether 56% of the building corners were reconstructed and identified to have an adjacency relation to at least one other corner. Using the CAG for indexing into parametrized buildings, the reconstructed 3d corners are sufficient for aggregating the 11 main building parts contained in the data set.

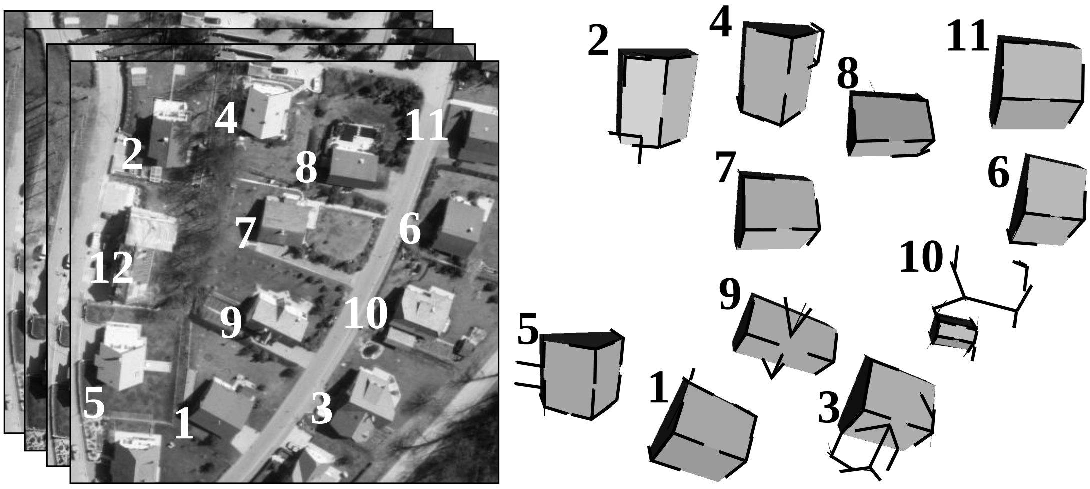

Fig. 8: Result of the building reconstruction procedure showing reconstructed corners in black and the aggregated parametrized building main parts.

This paper demonstrated the use of a hierarchical building model composed of semantically motivated building-specific components. Due to the close interaction of geometric and semantic reconstruction combining the mainly data-driven construction of model instances with the model-driven verification, the approach has the advantage that the maximum available knowledge can be exploited during all steps of the hierarchical reconstruction process.

The results have shown that by using 3d building corners, especially their semantics and their connectivity relations, the procedure does not require such strong constraints of a model with predefined building types. Therefore it enables to reconstruct generic buildings, especially if an additional intermediate level of building parts is introduced like it is described in Fischer et al. 1998.

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8 References

Fischer, A., Kolbe, T., Lang, F., Cremers, A., Förstner, W. & Steinhage, V. (1998): Extracting buildings from aerial images using hierarchical aggregation in 2d and 3d, *Computer Vision and Image Understanding* **72**(2): 185–203.

Fuchs, C. (1998): *Extraktion polymorpher Bildstrukturen und ihre topologische und geometrische Gruppierung*, PhD thesis, Deutsche Geodätische Kommission, München, Vol. C 502.

Heuel, S., Lang, F. & Förstner, W. (2000): Topological and geometrical reasoning in 3d grouping for reconstructing polyhedral surfaces, *International Archives for Photogrammetry Vol.XXXIII, B3/1, Comm.III, Amsterdam*, pp. 391–398.

Lang, F. (1999): *Geometrische und semantische Rekonstruktion von Gebäuden durch Ableitung von 3D-Gebäudeecken*, PhD thesis, Reihe Informatik, ISBN 3-8265-6619-X, Shaker-Verlag Aachen.