3D-SYMBOLIZATION USING ADAPTIVE TEMPLATES

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ABSTRACT:

For communication tasks adapted types of information are needed. In navigation, for example, landmarks play an essential role. In order to be able to recognize these landmarks immediately also from larger distances, unimportant details have to be simplified and relevant and characteristic features have to be visible. Thus, these characteristics should be highlighted or enhanced, which is a generalization function. We concentrate on building landmarks. In order to simplify and emphasize 3D buildings, the idea in this research is to use a generic set of templates for typical 3D-buildings and replace the original 3D shape with the most similar of those templates. In this paper, we briefly describe the whole workflow, but concentrate on the adaptation. For this adaptation process we propose optimization techniques. Depending on the target function to optimize, different approaches can be chosen, which will be described in the paper. The results using Least Squares Adjustment are presented.

1. INTRODUCTION AND RELATED WORK

Generalization of 3D objects is being tackled in Computer Graphics and many methods have been proposed to solve it; however, typically, the methods do not take specific object properties into account (Heckbert & Garland, 1997). In recent years, the generalization of 3D urban scenes has gained considerable interest and a variety of approaches has been proposed. The proposed methods mainly focus on the generalization of individual buildings, usually beginning from a highly detailed CAD models. For individual building generalization they use concepts borrowed from 2D-generalization attempting to reduce the geometric complexity of the 3D-shapes replacing their shapes by simpler versions. Forberg (2004) unites the advantages of mathematical morphology and curvature space in one process. The approach is based on “parallel shifts” and merge of two neighboring parallel facets whose distance falls below a predefined threshold. Such a “parallel shift” may lead to the simplification of all parallel structures including the split or merge of different object parts, the elimination or adjustment of local protrusions, step structures as well as box structures. Thiemann (2002, 2005) proposes segmenting complex buildings into their main parts and then interpreting and generalizing these parts in an object dependent way. Kada (2005) also starts from a segmentation of the whole building space into the parts defined by the faces of the building in a similar fashion as Thiemann (2002). However, Kada (2005) includes a flexible threshold that directly allows for a generalization and adaptation of faces of similar pose and direction. Lal and Meng, (2004) implemented an algorithm based on a hierarchical neural network to automatically recognize planar-structured building types. The recognized building type is further used as one of the input parameters of a classification of neighborhood relationships and thus the detection of building clusters. For groups of buildings, only very simple approaches like selective omission of some buildings are implemented, e.g., by Google Maps. More advanced recent approaches take context and scale into account to select what buildings to present (Omer et al. 2005).

The review of the state of the art reveals that generalization of 3D buildings is a relatively new research area where the focus was put on the generalization of individual buildings that try to preserve as much as possible the original shape. In contrast to this, we will concentrate on the generation of adaptive 3D templates that serve as a kind of 3D symbol, which, however, still resembles the original object in its important properties (e.g., a church with two towers should be represented with a template church that has this property).

2. 3D-ADAPTIVE TEMPLATES

The research presented in this paper concentrates on a specific generalization process, namely the emphasis of important individual 3D buildings (landmark objects), with their characterizing features in a way that they can be immediately recognized and understood. The idea is, that buildings can be categorized into a limited number of classes with characteristic shapes. Instead of presenting a specific building, a most typical representative of that class will be presented. In order to do so, the idea in this research is to use a generic set of templates for typical buildings and replace the 3D shape with the most similar of those templates. A comparable approach has been presented by Rainsford & Mackaness (2002) for the generalization of 2D-buildings. In contrast to their work, however, we are dealing with 3D objects, and we will not rely on a fixed alphabet of templates that only have to be scaled, but we have to define generic templates that can be composed of an arbitrary number of parameters (e.g. church is composed of n towers; each of them can be described by a cuboid with parameters a, b, c). Thus the challenge is the definition of the generic templates and the adaptation or matching process. For the adaptation, methods from homogenization will be applied, e.g. ICP (Besl and McKay, 1992) or 3D adjustment. The process is similar to an earlier work of building simplification in 2D (Sester, 2000).

The process of generating 3D adaptive templates consists of the following steps:

- Definition of elementary building types and their characterizing features

- Definition of a set of 3D templates (e.g. church towers, church body).
- Development of methods to recognizing the template features in the objects.
- Development of methods for adapting and optimally fitting the templates to the real object.

In the paper we will concentrate on the last step, namely the adaptation and optimal fitting of the given 3D model template to the original detailed building shape.

3. ADAPTATION PROCESS

3.1 Determination of 3D templates

The determination and selection of the templates can be pursued in two ways: on the one hand, an appropriate template can be selected based on the attributes of the object. This is similar to the 2D-map case, where, e.g. churches are assigned a certain building symbol in a given scale. On the other hand, if such a semantic assignment is not available or, if a lesser degree of generalization is searched, the templates can be generated based on a simplified form of the original object.

In our previous work we presented an approach to segment a 3D building into different parts based on geometric criteria (Thiemann, 2002). In a subsequent step, these parts can be assigned a meaning using a set of rules (Thiemann & Sester, 2005). The result of such a segmentation and interpretation step is a simplified version of a building, which is reduced to its main geometrically dominant shape. Thus, the coarse object is structurally and topologically similar to the original object, but geometrically there are large deviations. In order to fit this coarse shape – which can be interpreted as a simplified template – to the original building, an adaptation process has to be performed.

3.2 Representation of building model

The building is given in terms of a boundary representation. It is modelled as complex building, including details like roof structure, windows, doors, porches, chimneys, etc. An example for such a building is given in Figure 1.

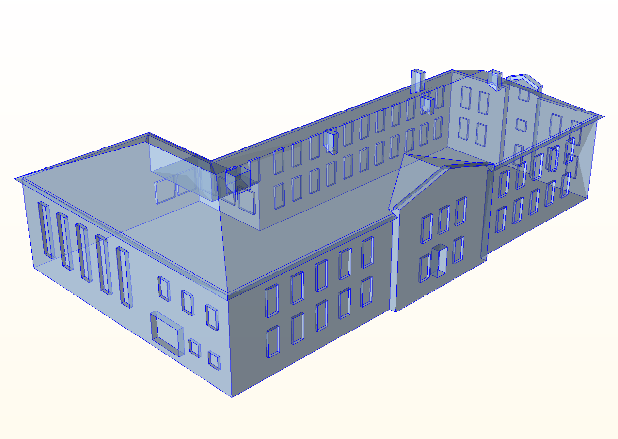

Figure 1: Example for original building modelled in full detail.

In our approach the individual boundary surface elements are represented with the plane parameters in Hessian Normal Form $\vec{n} \cdot \vec{x} = d$, where $\vec{n}$ is the normal vector and d is the distance from this plane to the origin of the coordinate system.

3.3 Adaptation process

The goal of the adaptation process is a optimal fit of the coarse template building (or prototype building) to the original object. An optimal fit can be defined as an adaptation where the differences in volume between the two shapes is minimized, or, the sum of the distances between the individual facades between the two representations is minimized.

The adaptation can be achieved by shifting (i.e. moving) of the individual planes. As the whole building is given in boundary representation, the topology between the adjacent planes is also preserved. However, to a certain degree also a change in topology can be achieved, e.g. when a general hipped roof is adapted to a saddleback roof: the general hipped roof consists of two inclined faces and a horizontal face on the top, whereas the saddleback roof is only composed of the two inclined faces. In this case, the horizontal face is reduced to a nearly vanishing face. For the adaptation, we experimented with two approaches, which will be described in the following.

3.3.1 Approach 1: Minimizing the symmetric volume difference

This approach aims at reducing the volumes that are different in the corresponding objects, leading to the fact that volumes extruding ($O \setminus P$) and intruding ($P \setminus O$) the objects are minimized. The functional is the following:

$$P \Delta O = P \setminus O \cup O \setminus P$$

namely, the difference between prototype (P) and object (O) united with the difference of original and prototype. Depending on the functional goal, two different results can be achieved:

a) Minimizing the maximum of both volumes leads to an adapted object with the same volume.
b) Minimizing the sum leads to a body with least differences.

The functional dependencies between the volume differences and the plane parameters can not be differentiated continuously. The differentials can only be determined numerically. Therefore, the optimum was calculated using the Downhill-Simplex-Algorithm.

The drawback of this approach is the bad convergence behavior. Furthermore, there can be several local minima that need not be an optimum. Therefore, we applied the strategy, that after a number of iterations, new start values were used for the next iterations steps. This sequence was repeated, until a minimal threshold was reached.

3.3.2 Approach 2: Minimizing distances between surface points

The idea of this approach is to discretisize the individual surfaces by points, find closest distances to the second surface and minimize these distances. In order to have a good representation of the original face by the point sample, the number of points have to be of an adequate size. Furthermore, the points have to be randomly distributed over the surface in order to reduce systematic effects. In order to achieve an equal distribution, however, without sampling the points evenly, we laid a raster over the surface and created a random point in each raster cell (see Figure 2). As we are using only a sub sample of potentially all surface points, the solution will only be an approximation. The higher number of sample points used, the better the accuracy will be, however, also the higher are the computational costs.

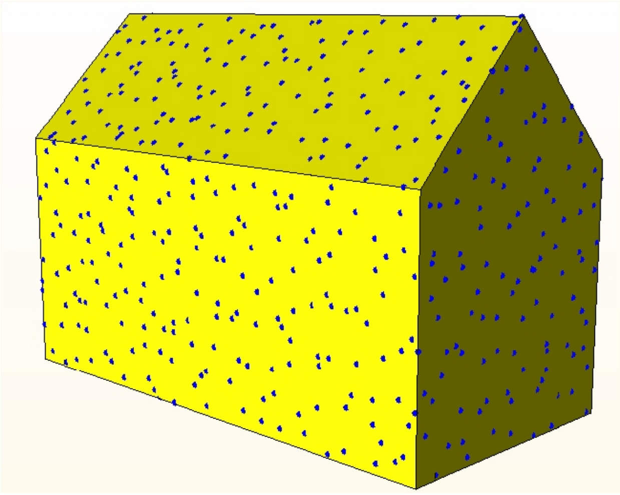

Figure 2: Equally distributed random sample points of the prototype and the original building

Convergence is guaranteed only when the surfaces of the prototype are attracted by the corresponding surfaces of the original object. This is the case, when approximate start position of the prototype lies within the 3D-middleaxis of the original object (see Figure 3).

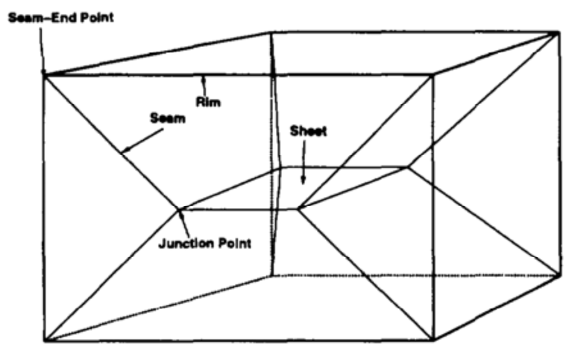

Figure 3: 3D-middleaxis (source: Sherbrooke, Patrikalakis & Brisson 1995)

As the functional dependencies between surface and corresponding point are straightforward, this approach can be solved with Least Squares Adjustment (Lawson & Hanson, 1974). The observations are the distances (see Figure 4), whereas the unknowns are the plane parameters, in this case only the distances of the plane from the origin (plane parameter *d*).

The dimension of the Jacobian matrix A is therefore corresponding to the number of surfaces of the prototype. No weights are used, leading to the simple form of the normal equation

$$d\vec{x} = \left(A^T A\right)^{-1} \cdot A^T \vec{l}$$

The elements of the A-matrix are determined by the derivative of the distance to the closest point from the prototype surface.

The derivative (d') is the quotient of the distance in normal direction of the plane (d_n) and the slope distance (d). The square of derivative of points with vertical distance is 1, points with horizontal distance have a derivative of 0. In the case, that prototype plane and the face of the original are coplanar, we have to consider if distance is 0 than the square of derivative is set to 1, in all other cases the derivative is 0.

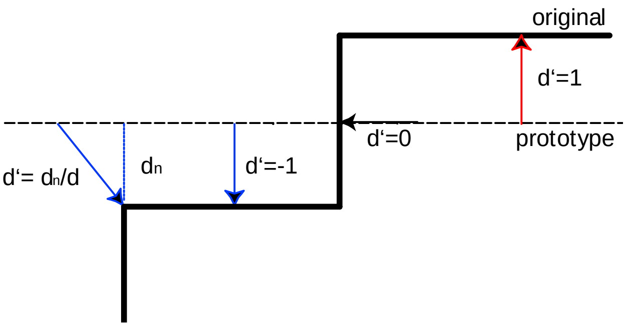

Figure 4: Distances and their derivatives.

$A^T \vec{l}$ describes the sums of the distances of the surfaces along the normal direction.

As every measurement (distance) is a function of only one unknown plane parameter, the normal equation matrix ($A^T A$) has only diagonal structure.. Therefore, the equation is simplified furthermore, leading to a direct solution:

$$d\vec{x}_i = \frac{\left(A^T \vec{l}\right)_i}{\left(A^T A\right)_{i,i}}$$

There are two ways to use this approach: either the prototype can be discretized and the shortest distances to the original object are calculated or vice versa.

The advantages discretizing the prototype are twofold: on the one hand, each distance is directly linked to a surface and its corresponding parameters, therefore, the distances do only have influence on this parameter. On the other hand, this approach also has a generalizing effect, as it does not respect small extruding volumes that stick off the original object (see Figure 5)

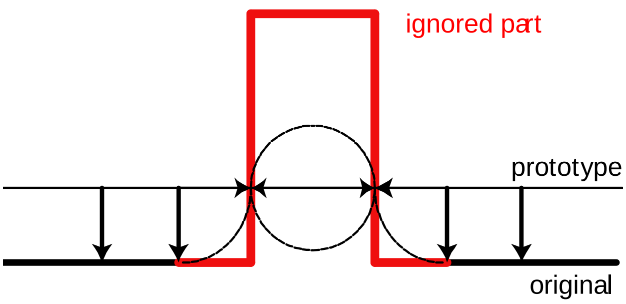

Figure 5: Generalizing effect due to distance measurement.

There are, however, also disadvantages: as the prototype and its surfaces are modified in each iteration step, the sampling has to be repeated in each step also. This leads to noise effects between the iterations. Furthermore, the point density has to be

high enough on order to compensate for the noise effect. The solution we took was to densify the sampling in each iteration – leading also to higher computational costs.
The (positive) generalization effect that reduces extended protrusions of the object, can also have a negative effect, as it leads to different local minima depending on the influence range of the distance operation.

The second option of discretizing the original object has the positive effect that the points have only to be determined once, as the original object does not change its shape during the iterations. Therefore, also no noise effects during the iterations will occur. However, it can happen, that there is not a unique correspondence of the point to the prototype surface (e.g. when the shortest distance is to an edge or a vertex of the object). Also, oblique faces have a higher influence on the result as parallel faces - in order to compensate for this, weights have to be introduced, leading to a more difficult structure of the normal equation system.

The advantage of using Least Squares Adjustment is that also additional constraints can easily be integrated in terms of observations. So one could think of including as additional constraint that the volume should be preserved. The disadvantage is, however, that the volume depends on all parameters, leading to a full equation system; furthermore, volume differences will be distributed equally to all surfaces – even to those that are coincident with each other.

4. EXPERIMENTS AND EXAMPLES

In the following, examples will be shown that were achieved using the Approach 2, namely minimizing the distances between prototype and original object. In all the examples, the original building is given in transparent blue, the adapted prototype is colored in yellow.

Figure 6 shows a simple building with windows, chimney and a gable roof with overhang on all sides. The prototype is also a gable roof, however without roof overhang. The result nicely shows the effect of the adaptation: the roof is fitted to the main roof parts, the short side walls are slightly moved outside – due to the roof overhang; also the front side is slightly moved inside, due to the effect of the windows, that sit back in the façade.

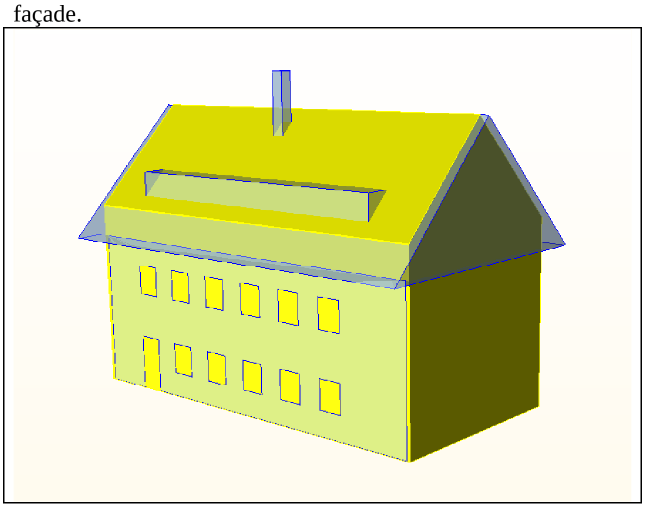

Figure 6: Adaptation of saddleback roof building.

Figure 7 shows the result when using a different prototype, in this case the generic hipped roof, consisting of three parts. In the adaptation process the two roof faces are adapted to the two original faces, leading to the earlier described effect that the horizontal top surface is nearly reduced to a line and thus vanishes.

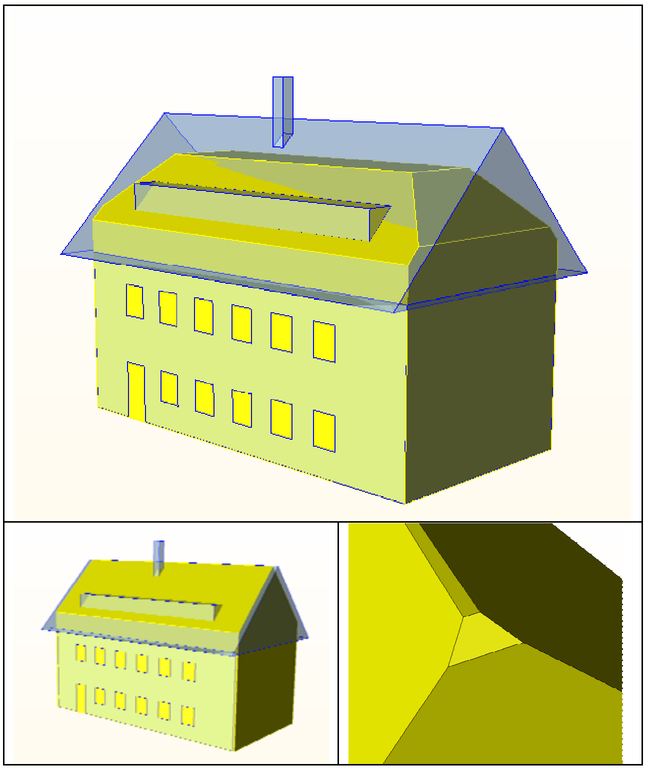

Figure 7: Generic template: original situation (above); after adaptation (lower left); enlarged detail of roof ridge - the top side is reduced to a width of 6 cm (lower right).

Figure 8 shows the adaptation of a U-shaped building: it is clearly visible, that the generalization effect in this case leads to the effect that one of the building sides is totally ignored, as the distance is no longer measured and taken into account.

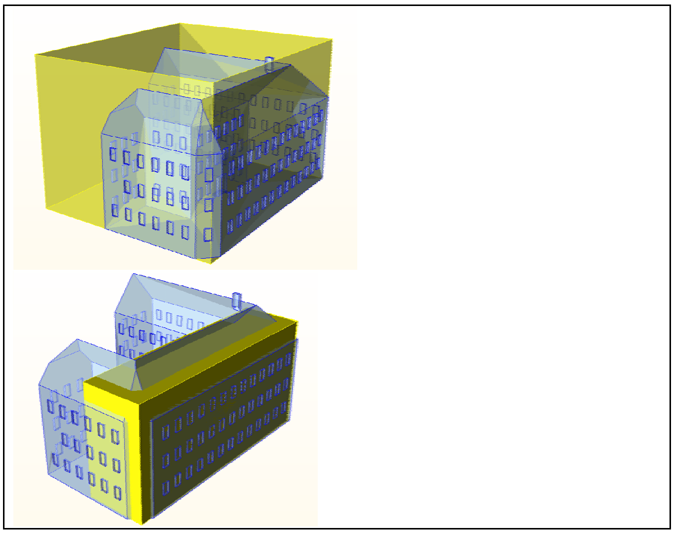

Figure 8: U-Shaped building

Figure 9 shows the result of a more complex building, that is nicely adapted to the given L-shaped template. The averaging effect of the adaptation process can be seen at the front part (lower left): the porch leads to the effect, that the prototype front is shifted in front of the original main part of the building.

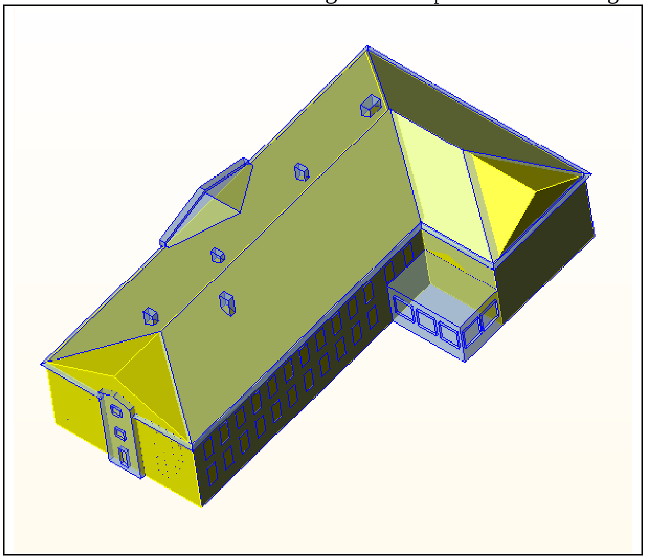

Figure 9: Complex building

In all the examples, the start situation was chosen in a way that the location of the prototype was within the original object according to Figure 3. Slight modifications of the start position did not have an effect on the final adapted model, in the case that there no local minima in consequence of the generalization effect.

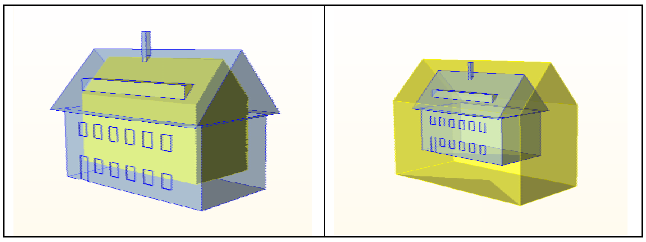

Figure 10: Modifications of the start position have no effect on the result (see figure 6)

The run-times for calculating the adaptation were as follows. For the simple building in Figure 6, the time was 4 seconds, for the building in Figure 8 it was 10 minutes, the building in Figure 9 it was 6 minutes. The runtime primarily depends on the complexity of the original object and the number of sample points. Secondly, it depends of the similarity of prototype and original.

5. SUMMARY AND FUTURE WORK

In the paper an approach has been presented that is able to optimally fit a template or prototype object to an original 3D building shape. Using the templates instead of the original object leads to a more compact, as simpler representation of the 3D object, and to a higher recognition rate, thus a more efficient communication of 3D objects.

There are several issues for future work. First of all, we will investigate, if the different optimization approaches described in the paper can be combined to yield a optimal solution. This will be achieved by minimizing the distances of all surface points by the error volume (instead of the distance alone).

Secondly, the generation of templates can be extended:

- Similar to the approach of Mackaness and Mackenzie, 1998, a (small) set of typical templates could be provided. In the adaptation process, all these templates would have to be fit to the original building and the one with the best fit (i.e. smallest deviations) would be selected.
- Another issue relates to a more sophisticated interpretation step in the beginning, leading to a semantic annotation of the object. Based on this semantic annotation, appropriate templates can be selected (e.g. L-shaped building, church, church with two towers, …).

Furthermore, we will use the approach to adapt models to laser scan data. For that case we use a discretized object – which is given by the laser points – and calculate the distances to the prototype.
Finally, we will investigate how certain constraints within the building template will be preserved or enforced, e.g. the fact that opposite facades of a building will have to be parallel or the same size.

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