A Data-driven Approach for Adding Facade Details to Textured LoD2 CityGML Models

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Abstract: LoD3 CityGML models (with facade elements, e.g., windows and doors) have many applications, however, they are not easy to acquire, while LoD2 models (only roofs and walls) are currently largely available. In this paper, we propose to generate LoD3 models by adding facade details to textured LoD2 models using a data-driven approach. The existing reconstruction-based methods usually require high costs to obtain plausible LoD3 models. Instead, our proposed data-driven method is based on automatically detecting the facade elements from the texture images and interactively selecting matched models from a 3D facade element model database, then deforming and stitching them with the input LoD2 model to generate a LoD3 model. In this manner, our method is free from reconstruction errors, such as non-symmetrical artifacts and noise, and it is practically useful for its simplicity and effectiveness.

1 INTRODUCTION

CityGML models enable representing the semantics of 3D cities at different levels of details (LoDs), so that users can choose a suitable city representation for their applications. An LoD3 CityGML building model not only inherits the simple exterior details of the building (i.e. walls and roofs) from its LoD2 representation, but it also contains more detailed exterior architectural structures (e.g., windows and doors). LoD3 representation is useful in many urban simulations (e.g., light pollution and shadow simulation). However, different from other CityGML representations with lower levels of details (LoD0, LoD1 and LoD2), which are largely available, only a limited number of LoD3 CityGML models are available. This is because the geometrical details on the outer surfaces cannot be easily reconstructed with a readily accessible pipeline.

Generally, there are three main approaches for generating LoD3 models. The first is to create LoD3 models from 3D point clouds directly (Akmalia et al., 2014; Hohmann et al., 2009). However, it usually requires high costs and many manual efforts to acquire, store and refine 3D point clouds in city scale. The second is to convert existing models of other formats, such as Building Information Models (BIM), to CityGML models (Geiger et al., 2015). However, the BIM data of a city is not always available. The third is to extend a model from LoD2 to LoD3 by adding 3D facade details on the planar surfaces (e.g., walls) of a building based on facade reconstruction using terrestrial laser scanning (TLS) data or the images of the buildings (Becker, 2011; Liu et al., 2017; Riemenschneider et al., 2012). However, this approach requires high costs and may introduce many reconstruction errors. Segmentation-based methods, such as (Riemenschneider et al., 2012), partition texture images into semantic image segmentations and then reconstruct the facade elements based on the segmentation results. By combining generic grammars and object detectors, reconstruction errors can be avoided, but these methods are constrained by the segmentation results, hence the quality of the texture images.

To the best of our knowledge, only a few works have been done to extend LoD2 models to LoD3 models and they usually require complex computations (Akmalia et al., 2014; Geiger et al., 2015; Becker, 2011; Liu et al., 2017). In this paper, a data-driven pipeline for extending a textured LoD2 model to a LoD3 model is proposed, where the facade elements are automatically detected, interactively selected and added to the textured LoD2 model input, based on its texture images (Figure 1). The goal of the pro-

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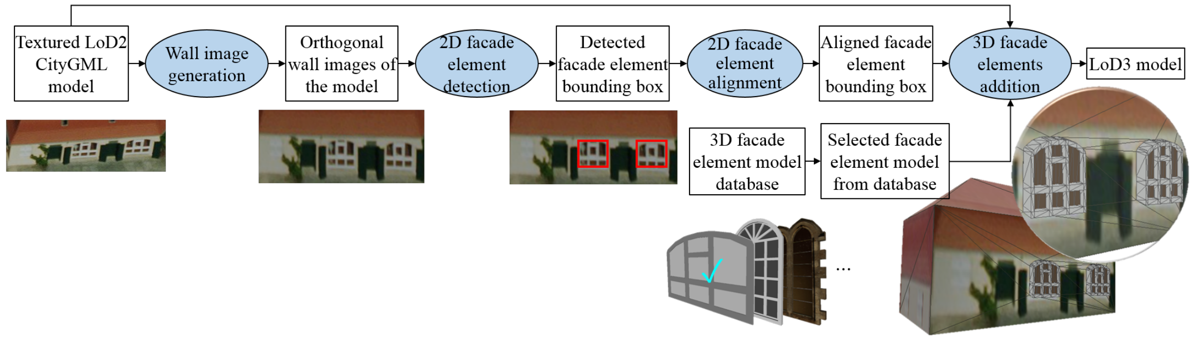


Figure 1: Our proposed pipeline illustrated using a window addition example.

posed pipeline is not accurate reconstruction of the detailed facade structures, but to generate plausible LoD3 models suitable for urban simulation (e.g., light simulation and wind simulation). Our method has the following contributions:

Contribution 1: facade element detection on low-resolution texture images is a non-trivial task. We propose a neural network approach that can automatically detect 2D facade elements from texture images.

Contribution 2: it is not easy to directly reconstruct the details of the facades. Many important properties such as symmetry might be lost due to reconstruction errors. There are many similarities among windows (doors), thus it is not necessary to reconstruct the same window (door) multiple times. Therefore, we propose to use a data-driven method by detecting 2D facade elements from the texture images and selecting matched 3D facade elements from a 3D facade element database. This can ensure that our generated model is free from reconstruction errors.

Contribution 3: the shapes of windows and doors are usually simple and regular. Therefore, we propose an effective facade element alignment and regularization method as well as an effective mesh deformation and stitching method to efficiently add windows and doors to the textured LoD2 model input.

Our method provides a simple and practical way of making full use of the available textured LoD2 models and adding facade details to the outer surfaces of the models.

2 OUR PROPOSED PIPELINE

The input of our LoD2-to-LoD3 generation pipeline is a textured LoD2 CityGML model. Our method generates polygon meshes of facade details, which can be combined with the input model to form an output LoD3 CityGML model. Figure 1 illustrates our proposed pipeline with an example, in which 3D window structure is selected and added to enhance the LoD2 building model input based on the window detection result of its texture image. 3D door structure can be handled similarly. In this paper, we mainly focus on adding windows and doors. Our pipeline has four main steps:

1. Wall image generation: wall images of the input textured LoD2 model are generated to facilitate better 2D facade element detection.
2. 2D facade element detection: the 2D facade elements are automatically detected from the orthogonal wall images of the input model.
3. 2D facade element alignment: redundant detection results are removed, and the detected 2D facade elements are processed to be well aligned and have the same size.
4. 3D facade elements addition: the selected 3D facade element models are deformed based on the detected 2D facade elements and stitched to the input model.

2.1 Wall Image Generation

(a) (b)

Figure 2: (a) An example in which a wall consists of two raw texture images taken from non-frontal views. We combine the areas enclosed by the red boxes together to form one piece of wall texture image. (b) The generated wall texture image for this example.

In real-world cases, it is very difficult to acquire high-quality wall textures for 3D building models in city scale. The raw texture images of many LoD2 CityGML models, e.g., Berlin's CityGML models

(Kolbe et al., 2005), are mostly broken and low-resolution photos taken from top or side views with overlapping and redundant parts. As such, the shapes of the facade elements in the raw texture images are distorted due to perspective distortion. Moreover, one wall and its facade elements may be divided into multiple raw texture images (Figure 2). These make the 2D facade elements hard to be detected and processed. Therefore, for each wall, one non-distorted and non-fractured frontal-view texture image is required, before running our other procedures.

To achieve this, we render each wall of the input textured LoD2 model into a texture image, using orthogonal projection. We make the virtual camera look at the wall center with its up direction aligned with the wall's up direction. By setting the size of the ortho view to the size of the wall, we can render and obtain orthogonal frontal view image of the wall. The generated wall images are used as the input for the subsequent steps.

2.2 2D Facade Element Detection

It is usually difficult to acquire high-quality wall textures for a city scale building dataset, for example in Berlin CityGML dataset (Kolbe et al., 2005), even after our preprocessing, the quality of the wall images are usually still low. In addition, in this dataset, most of the texture images already show over exposure or under exposure, i.e. the color range is minimized and leads to noise when adjusting the images with respect to the histogram. The inaccuracies in the texture images originate mainly from a combination of hardware restrictions and photogrammetric errors. Those are mainly the low image resolution, a restricted color range and incorrect exposure settings. Traditional object recognition methods (i.e. based on edge detection) are difficult to deliver desired results. Furthermore, deep learning techniques are currently largely available and are able to produce better object recognition results. As such, to tackle this 2D facade element detection problem, we use the pixel-wise object detection with Convolutional Neural Networks, which is based on the Mask R-CNN (He et al., 2017). We use the repository of (Abdulla, 2017) and make several changes to improve the inference result for orthogonal wall images. The general structure is shown in Figure 3.

We create a dataset of around 1,000 images for training. Because orthogonal wall images have different sizes and aspect ratios, we augment the orthogonal wall images in our dataset to square images using cropping or padding. We pad every orthogonal wall image and include it in the dataset. If the orthogonal

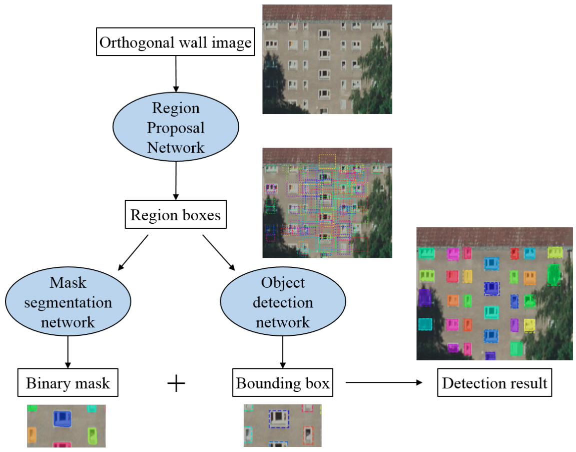


Figure 3: A neural network approach for detecting 2D facade elements.

wall image size is larger than our training image size, we apply cropping.

We use the ResNet backbone and apply transfer learning to adapt the network for facade element detection: we change the structure such that detection and classification is only made for facade elements, e.g., windows and doors. The first part of the network uses the Region Proposal Network (RPN) to enable fast region proposal. The RPN allows faster detection of possible facade element regions proposed for the next step. In the following steps, given the input image and region proposal, we determine the bounding boxes and masks for the facade elements. The detection of bounding boxes is independent of the mask segmentation. The bounding boxes are rectangles and cover the detected facade element. The masks represent the shape information of the detected facade element. As a resulting output, we have a binary image with the masked regions as well as bounding box coordinates. The overall loss function L is defined as follows:

$$L = L_{RPN} + L_{MRCNN} \tag{1}$$

$$L_{RPN} = L_{class-RPN} + L_{BB-RPN} \tag{2}$$

$$L_{MRCNN} = L_{class-MRCNN} + L_{BB-MRCNN} + L_{mask} \tag{3}$$

The Region Proposal Network's loss function contains the log loss $L_{class-RPN}$ for classes and the Smooth L1 loss L_{BB-RPN} for the bounding boxes. The Mask R-CNN loss function is the sum of the log loss $L_{class-MRCNN}$ for the classes, the Smooth L1 loss $L_{BB-MRCNN}$ for the bounding boxes and the pixel-wise binary cross entropy loss L_{mask} for the mask prediction. While the Region Proposal Network acts on the whole image, the Mask R-CNN only has the recommended regions as an input and therefore acts on subregions. Note that mask and bounding box generation are independent of each other. They do not rely on each other, but have the same input as received from the region proposal.

We minimize the overall loss function in order to detect the facade elements. Thanks to our subdivided structure, we can do so by minimizing each loss part separately. The classification loss minimization can help us to classify our desired category which is the facade element. RPN loss is crucial to minimize to get a more optimal region proposal indicating the potential facade element area. This region proposal is not based on color value gradients, which may lead to many more non-relevant features, instead, it focuses on capturing actual window complex. By minimizing the bounding box and mask loss, we can detect the location and shape of a facade element. We also use the mask to check and verify the results of the bounding box in terms of double detection. In some cases, one facade element is detected and split into two bounding boxes that are either touching each other or overlaying one another.

In contrast to common object detection networks, we do not use the average precision score as a criteria for improving the network, but the total number of correctly detected windows: we especially focus on improving the recall value for the bounding boxes. In other words, we prefer finding the exact amount of facade elements without detecting too many or too few facade elements to optimising the mask for pixel-wise correctness.We also adapt the detection threshold optimally such that most of the facade elements are detected and the error of false detection is minimized.

2.3 2D Facade Element Alignment

There are two forms of output for our 2D facade element detection step: 2D mask and bounding box of the facade elements. We use the mask results to check and verify the bounding box results. The detected 2D mask is also intended for generating detailed facade element contours, however, currently the detected 2D mask is too noisy due to the low quality of the acquired raw textures. Therefore, we choose to use the detected 2D bounding boxes to represent the facade element contours. In the future, we plan to improve our detection method to obtain detailed facade element contours.

As shown on the left side of Figure 4, most of the times, the detected facade element bounding boxes on one wall image are not of the same size, and they are also not well aligned. However, in reality, the windows on one wall normally (1) have the same size and (2) are well aligned in horizontal and vertical directions. To prepare a better input for the next step of adding 3D facade elements as well as for generating a natural-looking wall, we first delete the overlapping bounding boxes and then regularize the detection results based on these two heuristics.

Figure 4: The sub-figures on the left and right show an example of the original facade element detection result and the result after adjustment, respectively. In this example, $N_{cluster} = 3$.

(1) To ensure that the detected facade elements have the same size of bounding boxes, we first compute the average width and height, avg_w and avg_h, for all the detected facade element bounding boxes. Then for each single facade element bounding box, we subtract avg_w and avg_h from its width and height. Here we set a threshold for width and height difference, dif_w and dif_h (dif_w, $dif_h > 0$), based on the dimensions of the wall image. If the absolute difference between a facade element bounding box's width (height) and avg_w (avg_h) exceeds the specified threshold, we consider this element as an outlier and exclude it from the computation of avg_w and avg_h in the next iteration. We repeat this procedure until no new outlier is found, and then the finally obtained avg_w and avg_h are considered as the target regularized width and height for the facade elements. For the example in Figure 4, we set the threshold to 4% of the width and height of the wall image, and it took two iterations for the loop to converge. Generally, the loop converges within ten iterations when the threshold is set to be between 2% and 5%, since most of the detected bounding boxes are allocated regularly.

(2) To fulfill the second heuristic, we first compute the center for each facade element bounding box, c_{ix} and c_{iy} ($i = 1, 2, \ldots, N$) in horizontal and vertical directions. Based on these values, we adjust the facade elements in horizontal and vertical directions. Here we take the x direction adjustment as an example to illustrate our method. We first sort the facade elements based on their c_{ix} values in ascending order. After that, we apply a rule-based clustering algorithm to segment them. Then, we adjust the center positions of all the facade elements in one cluster to the same x value (c_x).

The rule-based clustering is as follows: for the

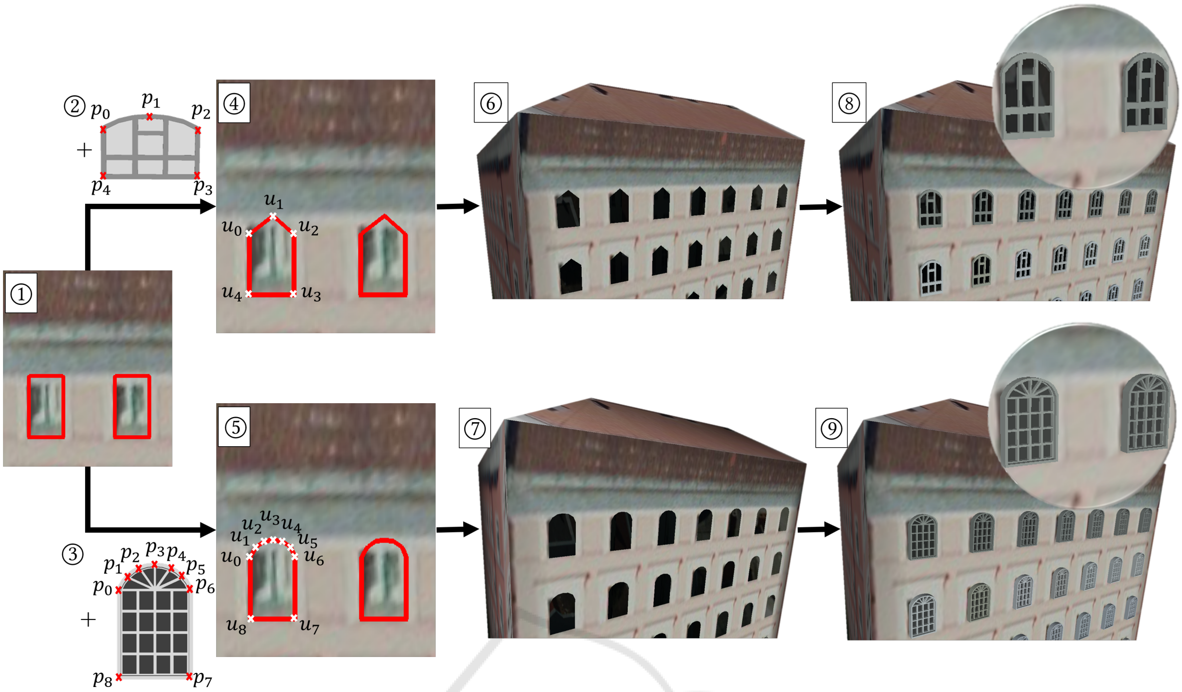


Figure 5: When choosing a 3D facade element model from the database, we also obtain the 3D feature points which define the boundary of this model. Suppose that the window detection output is ①. If we choose ② as the matched window model, then we will have the corresponding feature point result in ④. By cutting holes following the computed feature points, we obtain ⑥, and ⑧ is the enhancement result with window ②. Likewise, if we choose ③, then ⑨ is the enhancement result.

sorted version of c_{ix} $(i = 1, 2, \ldots, N)$, we compute the difference $|d_{ix}|$ between the adjacent elements (for $i = 2, \ldots, N$, $d_{ix} = c_{ix} - c_{i-1x}$, and for $i = 1$, $d_{ix} = 0$). If one facade element has a $|d_{ix}|$ greater than dif_w, we apply a segmentation and consider this facade element as the start point for a new cluster. Then for each cluster, we find the rounded average of the c_{ix} values and use it as the center x value (c_x) for the facade elements in this cluster.

We also apply the same method to c_{iy} in y direction. In this manner, we adjust and align the center positions for all the facade elements. Note that we allow users to define a threshold $N_{cluster}$ for the cluster size. For those clusters whose sizes are smaller than $N_{cluster}$, their facade elements are marked as irregular shapes, and the computed regularized width and height would not be applied to them. The right side of Figure 4 shows such an example in which the irregular facade element is enclosed in a blue box.

Besides adjusting the detection results, we also provide the users a heuristic approach to identify doors in this step, so that a different 3D facade element model can be selected for the doors in the next 3D facade elements addition step. Our door identification is based on the common sense that the doors are usually the nearest to the ground among all kinds of facade elements. Therefore, if the distance from the lower line of the bounding box of a facade element to the ground is approximately zero, we identify this facade element as a door. For the example in Figure 4, the facade element enclosed in blue box is identified as a door.

2.4 3D Facade Elements Addition

Based on the detected facade elements, we interactively select matched 3D facade element models from a 3D facade element database. In this database, the model definitions include the basic geometry information of the models and also the feature points for defining the 3D boundary of the models. We resize and align the selected 3D models according to the detected 2D bounding boxes, to ensure that they have the same locations, orientations and sizes. This computation is done in the following way: we first transform the 3D facade element models to align them to the target wall. This step guarantees that the models face the same direction as the wall, i.e. have the same normal. Then we position the 3D models to the centers of the detected 2D bounding boxes, and resize them to match their bounding boxes with the detected bounding boxes. By doing these three steps, i.e. transformation, position and resizing, these 3D facade element models are located in the desired places on the target wall as the detected 2D bounding boxes.

After that, based on the feature points on the boundary of the selected 3D facade elements $\vec{p}_i$ ($i = 1,2,\ldots,M$) (provided in the model definitions), we compute the corresponding feature points $\vec{u}_i$ ($i = 1,2,\ldots,M$) on the detected 2D bounding boxes (we lift these points to 3D using the walls depth value). We also cut holes in the walls of the input LoD2 model following the boundary defined by $\vec{u}_i$. This step is illustrated in Figure 5.

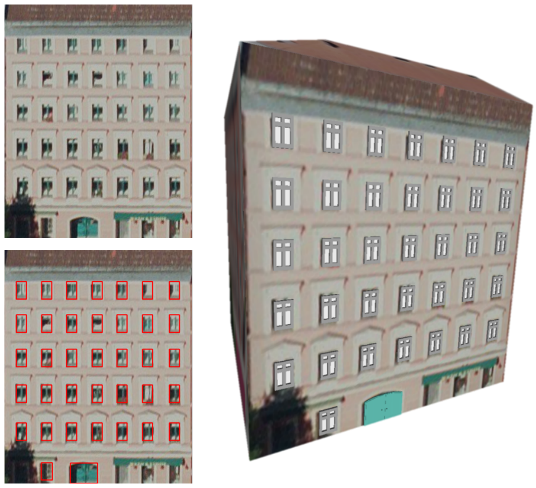
We then deform the selected 3D facade elements to align with the detected 2D facade element bounding boxes in a way that the pairs of feature points coincide with each other. To achieve this deformation, we adopt the radial basis function interpolation method. We build three linear equation systems using the M pairs of feature points ($\vec{p}_i$ and $\vec{u}_i$) to compute the x, y and z coordinates of the deformed position $\vec{u}$, respectively. We take the computation for the x coordinate of $\vec{u}$ as an example:

$$u_{ix} = \sum_{j=1}^{M} a_j g(\|\vec{p}_i - \vec{p}_j\|) + c_0 + c_1 p_{ix} + c_2 p_{iy} + c_3 p_{iz}, \quad (4)$$

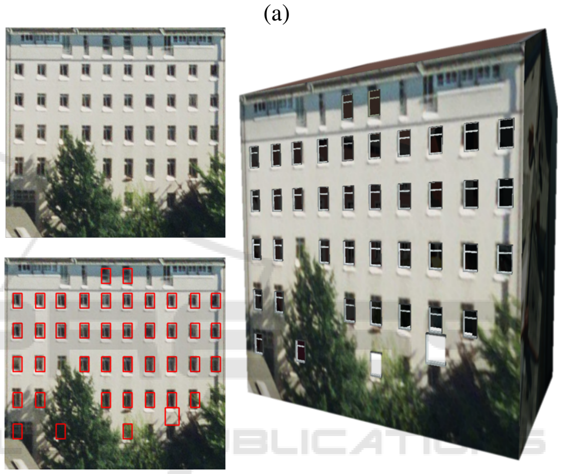
$$\sum_{j=1}^{M} a_j = 0, \sum_{j=1}^{M} a_j p_{jx} = 0, \sum_{j=1}^{M} a_j p_{jy} = 0, \sum_{j=1}^{M} a_j p_{jz} = 0 \quad (5)$$

Here $g(.)$ denotes a radial basis function, and in our implementation, we use $g(x) = \sqrt{\log(1+x^2)}$. The weights a_i and the coefficients c_0, c_1, c_2, c_3 can be obtained by solving this equation system (Equations (2) and (3)), then they are substituted back to Equation (2) to form the deformation function: $u_x = \sum_{j=1}^{M} a_j g(\|\vec{p} - \vec{p}_j\|) + c_0 + c_1 p_x + c_2 p_y + c_3 p_z$. This function takes $\vec{p}$ as input and computes the x coordinate of its deformed position $\vec{u}$. Likewise, we compute the y and z coordinates of $\vec{u}$. By doing so, we deform the 3D facade elements to align with the the detected 2D facade element bounding boxes on the wall images. After this, we stitch them back with the LoD2 model to generate a LoD3 model by merging the overlapped feature point pairs.

We also propose a method to fix the colors of the 3D facade elements, i.e. to adjust the colors of the 3D facade elements based on the original colors of the 2D target facade elements in the wall image. We cluster the colors from the 2D target facade element into two, using K-means clustering. The cluster size is set to two, because most of the facade elements that we are currently dealing with are windows, and they normally have different colors for frames and glass panes. Based on this, we select the dominant color in each cluster and assign it to the frame part or the rest part of the 3D model (differentiated based on the material definition), respectively.



(a)



(b)

Figure 6: Examples of the generated orthogonal wall textures (top left), the detected and aligned 2D bounding boxes for the facade elements (bottom left) and the LoD3 building output (right).

3 RESULTS

As shown in Figures 1, 5, 6, and 9, our method can effectively add details to textured LoD2 building models. All the models and texture images used in the examples are from Berlin's CityGML model (Business Location Center, 2018). In Figure 6, the input wall textures, the detected and aligned 2D facade element bounding boxes and the enhancement results are shown side by side for comparison. Based on the detected 2D facade elements, our alignment and addition methods can generate a visually plausible LoD3 building model. A snapshot of a virtual street scene in LoD3 is presented in Figure 9 to demonstrate our enhancement results on a street level.

Since the raw texture images of many LoD2

(a) (b) (c)

Figure 7: Examples of facade element detection results.

Figure 8: Decorate a LoD2 model with different windows.

CityGML models are of low resolution, it is hard to retrieve all the geometric information of the facade elements from one single texture image. In Figures 2, 6 and 7, we can see that the wall textures were taken under different illumination and view angles. Despite that we can generate orthogonal front view wall images as the input for the enhancement, the images of the facade elements still suffer from distortion, low resolution and shading problems. In this case, the reconstruction-based methods are not suitable. By contrast, the proposed pipeline avoids these problems by generating regularized contours based on detecting bounding boxes, applying simple geometry rules, and incorporating information from our 3D facade element database.

Figure 7 shows a typical output for our 2D facade element detection step. We computed the recall and precision in terms of the detected windows: positive (negative) means that this object is classified as (not) a window. True positives are the correctly detected windows while false positives are the incorrectly detected ones. The high recall rate means that we only have very few false positive cases in our detection, which guarantees proper input for the alignment and addition procedures. For the 36 wall texture images that we have tested on, we can achieve a recall of 94% and a precision of 83%.

For 2D facade element detection, the training and detection is on a PC with 8 GB GPU. With an average of 34.3 windows per facade image, our average evaluation time is 2.25s per image. While the fastest prediction is made in 1.6s, the slowest inference is made in 4.6s. For a generated wall image, its facade element detection result is saved in a JSON file. For all the enhanced building examples in this paper, the alignment and detail addition procedures were implemented on another PC with 8-core CPU working at 2.60GHz. With a wall image and the corresponding JSON file as input, the average alignment and detail addition time for a building model was around 1s, which excluded the interactive 3D facade model selection time and the alignment threshold set time. This average time was computed based on the examples presented in this paper.

Besides constructing a LoD3 model based on the wall textures, the proposed pipeline also can be applied to decorate a textured LoD2 model using user desired 3D facade element models (Figure 8). In addition, we can decorate a user specified 3D facade element to any location as user desired.

4 CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a data-driven approach for adding facade details to a textured LoD2 CityGML model. Different from the existing reconstruction-based LoD3 model generation methods, our approach tackles this problem by detecting, interactive selecting, deforming and stitching 3D facade element models to obtain a plausible LoD3 model for the input LoD2 model. Some results are provided to show how the proposed pipeline works.

For now, the 3D model selection is done manually. We plan to tackle this problem in a more efficient and deformation-friendly manner, considering that facade elements, such as windows and doors, usually have symmetrical and regular geometries. In this way, the correspondence between the detected 2D contour and the boundary of the retrieved 3D facade element model can be easily established for the deformation. In addition, despite that in the 2D facade element alignment step, clustering is applied to classify the detected windows into different groups, currently we do not consider this information when selecting the 3D models for the windows, i.e. we use the same window model for all the windows. We will include this information in the automatic 3D model selection plan to improve the plausibility of the output LoD3 model. The style of the buildings would also be considered for more aesthetically pleasing results.

Because of the complex u-v coordinates of the original CityGML model, the rendered facade images still contain some parts of the rooftop, neighboring houses partially, and a variety of trees. As such, the detection algorithm sometimes fails to detect or gives wrong detection results when there exists occlusions. We plan to incorporate the detection of those additional objects in the future, to clean up the facade images and guarantee a better quality of the results.

Currently our database only contains 3D window

Figure 9: A virtual street scene in LoD3 built by enhancing LoD2 models using our proposed pipeline.

and door models. In the future, more facade element models, such as balconies and chimneys, will be included. We are also working on making this process more intelligent and comprehensive by incorporating more advanced shape classification and deformation procedures into our pipeline.

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