Generation of 3D Building Models from City Area Maps

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Abstract: In this paper, we propose a pipeline that converts buildings described in city area maps to 3D models in the CityGML LOD1 standard. The input documents are scanned city area maps provided by a city authority. The city area maps were recorded and stored over a long time period. This imposes several challenges to the pipeline such as different font styles of typewriters, handwritings of different persons, varying layout, low contrast, damages and scanning artifacts. The novel and distinguishing aspect of our approach is its ability to deal with these challenges. In the pipeline we, firstly, identify and analyse text boxes within the city area maps to extract information like height and location of its described buildings. Secondly, we extract the building shapes based on these locations from an online city map API. Lastly, using the extracted building shapes and heights, we generate 3D models of the buildings.

1 INTRODUCTION

A 3D model of a city is a valuable tool for city authorities to plan new construction projects. In the past, city planning was done using hand drawings and typewriters. Therefore, for many older city areas there is no digital data available which can be utilized by 3D modeling and rendering tools. Usually, creating 3D models of buildings in these areas is done manually which is time consuming and costs lots of efforts. In this paper, we propose a pipeline to generate 3D building models automatically based on archived city area maps provided by city authorities.

Our input city area maps contain streets, smaller overview maps and buildings with detailed shapes. A couple of these buildings are marked. For the marked buildings, several text boxes, distributed around the map, add various additional information. The input in Figure 1 shows an example city area map. These maps pose several challenges for automatic document analysis. As they are often maintained over a long time period, they exhibit different font styles of typewriters and many different handwritings. Furthermore, the general layout of the documents varies as well. For example, the text boxes with additional building information can appear at arbitrary locations. In addition, long storage in archives may lead to low contrast and damages. Making the city area maps available to digital processing by scanning can yield to additional artifacts.

The novelty of our approach lies in its robustness to deal with these challenges. The output of our pipeline is a list of 3D models for all the marked buildings in the city area maps. We use the CityGML standard (Gröger et al., 2012) with level of detail (LOD) 1 to store our models.

LOD1 is used for simple building models with no details which are, however, sufficient to get an overview of a city area. The output in Figure 1 shows an example for CityGML LOD1 models. Whenever we use the term 3D model, we mean a model according to this standard.

This paper is structured as follows. Section 2 summarizes related work. Section 3 gives an overview of the proposed pipeline. Subsequently, in Sections 4, 5 and 6 the different parts of the pipeline are described in detail. Finally, Section 7 summarizes our results and outlines future work.

2 RELATED WORK

Previous work related to the analysis of city area maps focused on the analysis of floor plans of single buildings (Ahmed et al., 2011) or the automatic detection of rooms in floor plans (Ahmed et al., 2012). In the context of 3D building model generation (Sugihara et al., 2015) proposed a pipeline to automatically

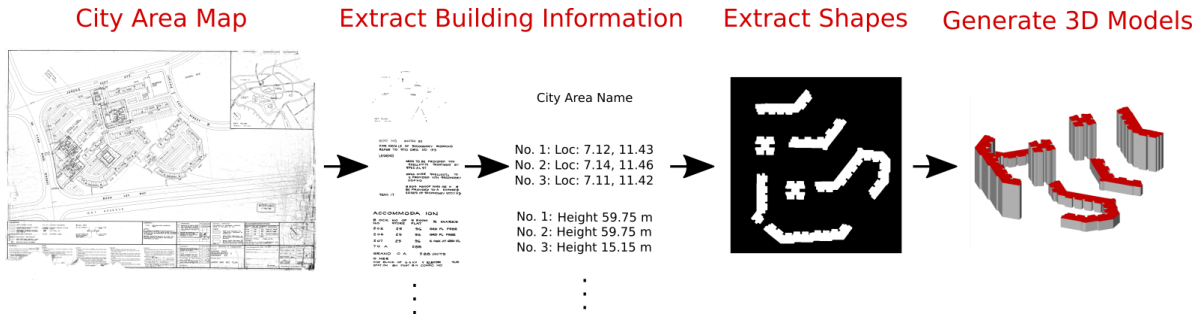


Figure 1: Overview of the proposed pipeline. The input is a city area map with text boxes describing several marked buildings. First, the content of the text boxes are analysed and information like location and height for all marked buildings extracted. Afterwards, using the locations, the shape of the buildings are extracted from an online city map API. Finally, 3D models are generated based on the shape and height information.

generate models based on polygons which have been manually marked on a 2D digital map before. (Biljecki et al., 2017) also investigated the generation of building models with a low level of detail. Their approach uses building footprints, additional information about the building and statistical data to deduce the height and shape of the buildings. A variety of approaches have been developed for the reconstruction of very detailed building models based on photo and laser scanning data. An overview can be found in (Fritsch and Klein, 2018). Furthermore, the CityGML standard (Gröger et al., 2012), used to store the resulting 3D models of our pipeline, is itself focus of ongoing research (Biljecki et al., 2016).

The text analysis methods used in Section 4 are related to previous work in text detection and recognition. Comprehensive surveys of this area can be found in (Ye and Doermann, 2015) and (Zhu et al., 2016). Most recent approaches which are able to deal with challenging scenarios are based on deep neural networks (Jaderberg et al., 2016), (Bartz et al., 2017a), (Zhou et al., 2017), (Liu et al., 2018). They exhibit impressive results in terms of accuracy and robustness to variations of image quality, illumination, text fonts, rotations and distortions. They, however, also heavily depend on large image data sets with appropriate labeling. The previous approaches which are most relevant to ours rely on manually designed features like extremal regions (Neumann and Matas, 2010), (Neumann and Matas, 2012) or stroke width measures (Epshtein et al., 2010). They first seek character candidates using the features and rely on post processing and classifiers to filter out the true characters. Due to the unique character of the input city area maps and the consequential lack of appropriately labeled data we chose a similar approach to (Neumann and Matas, 2010) for the text analysis part of our pipeline. We also extract maximally stable extremal regions (MSER) and use post-processing and a classifier to detect true characters. An additional argument for this approach is the availability of an open-source implementation for the MSER extraction (Bradski, 2000).

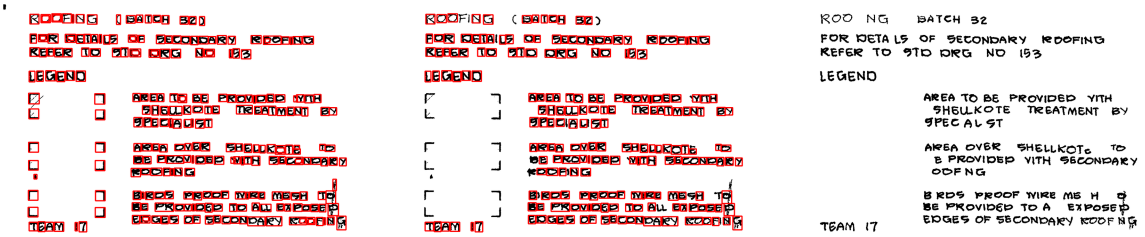
3 OVERVIEW OF THE PROPOSED PIPELINE

We propose a pipeline that converts buildings in a city area map to 3D models in the CityGML LOD1 standard. The overview of this pipeline is illustrated in Figure 1. The input are scanned versions of archived city area maps provided by city authorities. These maps contain among others a couple of marked buildings which are described in more detail in several text boxes. We assume that these text boxes contain information about the location and height of the marked buildings. The provided city area maps show a large variation of quality, style and layout. We, therefore, invested a lot of effort to make the proposed pipeline robust to this versatile input. Our approach can be divided into three parts. For all marked buildings in the city area maps, we

1. use text analysis to extract the location and height from the text boxes describing the building (Section 4).

2. search the location with an online city map API and extract the shape from the resulting city area image (Section 5).

3. generate a 3D model using the extracted shape and height (Section 6).



(a) Result of finding text character candidate regions using MSER (Matas et al., 2002). Each detected region is marked with a box.

(b) Text vs non-text classification result. The classifier correctly finds most of the text boxes while excluding non-text elements.

(c) The same text box after extracting the regions classified as text characters.

Figure 2: Example for the text extraction for a segmented text box of a city area map.

4 BUILDING INFORMATION EXTRACTION

This section describes the extraction of the location and height information of buildings in the city area maps. The input are the previously described city area maps. Several text boxes, distributed at arbitrary locations in the maps, add additional information for a couple of marked buildings. However, these text boxes contain many non-text elements as well. This makes it impossible to process them with Optical Character Recognition (OCR) software directly. The non-text elements can be of arbitrary nature. Typical are drawings, diagrams, grid cells, separation lines, noise and artifacts due to the scanning process.
Our approach therefore contains several steps:

1. Segmenting the text boxes in the input maps (Section 4.1)
2. Extracting candidates for characters in the text boxes (Section 4.2)
3. Classifying these candidates into text or non-text (Section 4.3)
4. Recognizing the content of the characters classified as text (Section 4.4)

4.1 City Area Map Segmentation

We segment the full city area map into smaller parts containing the text boxes and fragments of the map. Our method uses simple image statistics. We extract long horizontal and vertical lines from the map using a rank filter (Soille, 2002). This results in an image containing mainly the separating lines of the text boxes. The city area maps have been binarized during the scanning process. Therefore, to find the location of the lines separating the boxes, we simply count the black pixels per line and column. We smooth the resulting pixel count curves to make our approach robust to noise and small rotations in the documents.

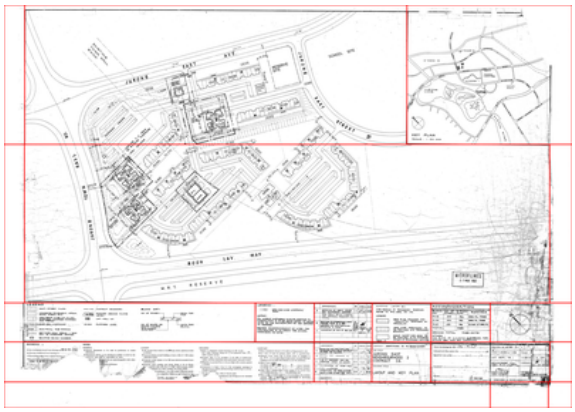


Figure 3: Example for a city area map segmentation result. The segments mainly align with the text box borders. The segmentation of the map area is irrelevant because the target information is contained in the text boxes only.

Finally, we create a histogram of all pixel count maxima. The highest p percentile of the maxima count values are considered to be separating lines with p being an empirically determined hyperparameter of our approach. The result of this method applied on a typical city area map is shown in Figure 3.

4.2 Character Candidate Extraction

After the image segmentation, we continue processing each segmented text box separately. To get possible candidates for characters we first apply a median filter to denoise the text box. Afterwards, we extract the candidates using the maximally stable extremal regions (MSER) algorithm (Matas et al., 2002). The output of this method are regions surrounding possible characters. Figure 2a shows an example where each detected region is marked with a box. These regions are eventually extracted resulting in an image containing only the parts within the regions.

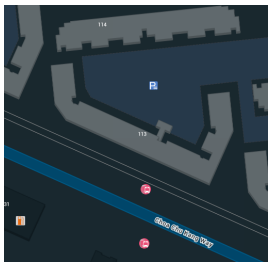


Figure 4: Image retrieved from the new OneMap Static Map API by the center coordinates of Block No.113.(NewOneMap, 2018)

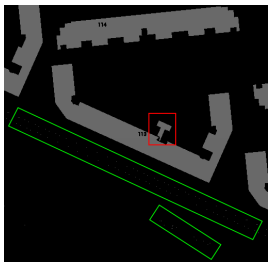


Figure 5: Thresholding result with a contiguous noisy object indicated in red rectangular.

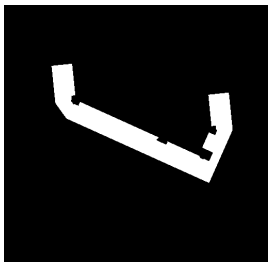


Figure 6: Extracted shape of the target building.

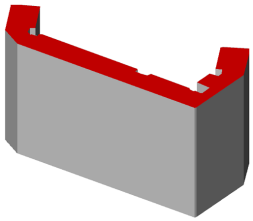


Figure 7: Result of the 3D model generation for the shape shown in Figure 6.

4.3 Text vs. Non-Text Classification

Identifying which character candidates are real alphanumeric characters or not is a typical binary classification problem. To solve it, we experimented with a couple of machine learning models ranging from Logistic Regression, Support Vector Machines to Convolutional Neural Networks (CNN). To train these models we, however, needed to first create a data set. We therefore took a subset of all character candidates and manually labeled them to be alphanumeric or not. The result was a data set with 12602 images of which 54% represented real alphanumeric characters. Afterwards, we trained the different models on this data set. So far, we achieved the best classification results on a hold-out test set with a simple VGG-like CNN (Simonyan and Zisserman, 2014). An example of applying this classifier on a text box containing the extracted character candidate regions can be seen in Figure 2b. The boxes mark characters identified as alphanumeric. Extracting only the regions of the characters within these boxes yields Figure 2c.

4.4 Text Recognition

The resulting text boxes containing the plain text only can finally be used as input for an Optical Character Recognition (OCR) software. There are several OCR tools designed for this task (Smith, 2007), (Breuel, 2008). Furthermore, there are deep learning approaches which could also be utilized (Shi et al., 2015), (Bartz et al., 2017b). As we deal with texts containing several different font styles and handwriting, we need to fine-tune a model for an OCR software or deep learning architecture to our data. This is still work in progress and the only yet missing part of the pipeline.

The result of these tools is the text content of the text boxes in the city area maps. This content can hence be processed by standard text search engines. The location and height information in the provided city area maps are indicated consistently across the whole data set by the same keywords. One can therefore search the text content for these keywords to find the location and height for each described building. This will serve as input for the following parts of the pipeline.

5 BUILDING SHAPE AND SIZE EXTRACTION

5.1 Shape Extraction

In order to generate the 3D model of a target building, whose location and height information are obtained from text extraction and recognition as described above, the next step is to get the building shape and size. However, processing a city area map as shown in Figure 3 may lead to less accurate building shape and size. This is because some of the old maps were drawn by hand and afterwards digitalized by scanning. Hence, inaccuracies due to the limitation of human drawing precision, the thickness of the pen and other undesired noise is inevitable. Furthermore, dealing with such complicated noisy images generally means longer computational time.

Due to the aforementioned reasons, instead of using the original archived city area map, our method extracts a more accurate building shape and size in a faster way by leveraging an online API, which is the new OneMap API. Specifically, we used new OneMap Search API and Static Map API (NewOneMap, 2018). The Search API returns the coordinates of a building based on its address. The Static Map API returns an image of a map section

Figure 8: Image of a large neighborhood retrieved from the new OneMap Static Map API. (NewOneMap, 2018)

Figure 9: Extracted shapes of the target buildings in a large neighborhood.

based on some pre-defined parameters such as image center coordinates, zoom level, image size and so on.

Figure 4 shows an example image retrieved by the API based on the center coordinates of a certain building. (Block No.113, which is the target building in this case.)

For the purpose of getting as many details as possible, we use the maximum zoom level and the biggest image size provided by the new OneMap Static Map API. Only a grayscale version of this image will be processed later. Dealing with such an image will lead to much more accurate building shape and scale as well as a much shorter processing time compared to working on a noisy and possibly damaged archived plan.

In the retrieved images of the new OneMap Static Map API, all buildings of interest, which are the public housing buildings, have the same grayscale value. Hence, one simple thresholding operation is able to segment all of them successfully. Then, we can get the target building boundary shape based on the contour characteristics of all the objects left after thresholding. Firstly, we remove all the objects whose contour area is small. The main purpose of doing this is to get rid of contiguous objects around the target building. According to the original city area map, these objects are surrounding constructions, which are not part of the target building. Figure 5 illustrates such an object among all the segmented building candidates by drawing a red box around it. Additionally, small building parts cropped along the image boundary and other noise sharing the same grayscale value (small dots below Block No.113 in the green boxes in Figure 5) are eliminated as well. Secondly, we pick the object whose contour centroid is the closest to the image center among all the remaining objects as the target building. As mentioned before, the target building center coordinates are returned from the new OneMap Search API then passed to the new OneMap Static Map API. The Static Map API uses these coordinates as the generated image center. Therefore, the target building centroid and the image center overlap in most of the cases in which the building has a regular shape. Finally, the shape of the target building is extracted based on the detected contour. The result is shown in Figure 6.

5.2 Size Computation

Since a fixed zoom level is used in the new OneMap Static Map API for generating the images, we can compute the actual size of the building based on the scale corresponding to this zoom level. Later, by combining the computed actual size of the building planar with the extracted building height from text analysis part, we are able to generate the 3D building models with correct ratio. The advantage of this method is that the scale is universal for all buildings if the zoom level is unchanged, as in our case. This is extremely useful for creating 3D models of a large neighborhood. Conversely, for the archived city maps, the scale used for drawing may change from map to map. When creating 3D models for all buildings in a large area or even a whole city, several maps with different scales may be used. As a consequence, extra effort is needed to align the scales between different maps if we directly extract the building shapes and sizes from the archived city area maps.

6 3D MODEL GENERATION

Based on the shape and the size information from Section 5, we first refine the extracted shape of a building ground print using image processing operations (dilation, erosion and contour retrieval). We then extrude it to 3D using the height information from Section 4. As such, we can generate 3D models for all buildings described in the input city area map. An example of a resulting 3D model is shown in Figure 7.

Figure 8 shows a big neighborhood retrieved from the new OneMap Static Map API and Figure 9 shows the extracted shapes of all the target buildings in this neighborhood by our method. As described above, with the size and height information we can generate 3D models of these buildings with correct ratio. Figure 10 and Figure 11 give illustrations of the 3D building models in such a big neighborhood from two different views.

7 CONCLUSIONS AND FUTURE WORK

We have proposed a pipeline to automatically generate 3D building models based on archived city area maps. The pipeline is still in the middle of implementation as the text recognition part, described in Section 4.4, is still in development. We, however, showed results for the automatic extraction of text from the city area maps such that it can serve as input for typical OCR tools. During that, we showed how to deal with the challenges of the input maps. We demonstrated how to segment text boxes from non-text areas and how to separate text characters from other elements like noise or drawings. Furthermore, assuming that we find the location and height information, we showed how to extract the shape and size of buildings using the new OneMap APIs. Finally, we presented results for generating 3D building models using the height, shape and size information.

The novelty and challenge of our approach is that it leverages generally available data sources which are however not primarily designed for the generation of 3D building models. The building information is obtained from scanned analog maps and the shape deduced from an online city map which contains much more content irrelevant for the task. In contrast, the approach in (Sugihara et al., 2015) relies on additional polygons added to a digital map. The building information like number of stories is also provided digitally for each polygon. In (Biljecki et al., 2017) plans containing solely building footprints and a digital database with additional information about each building is used. Therefore, compared to our approach, the usage of text detection and recognition is not necessary and both are able to deliver more detailed results. The building models in (Sugihara et al., 2015) have a higher level of detail because of the detailed annotations in the polygons and in (Biljecki et al., 2017) the height estimation is more precise, due to the combination of several data sources.

The limitation of the building information extraction is that some characters like 'i', 't', 'j', 'l' and '1' are difficult to differentiate from the noise in the maps. As a consequence, the current classifier tends to exclude these characters which are therefore often missing in the extracted text. We plan to fix this issue by adding more examples for these cases to our training data set. Besides that, to complete the implementation of the pipeline, we are still working on fine tuning an OCR model to recognize the extracted text. To do this, we need to create a second data set containing the extracted words and sentences and manually label them with the correct text content.

For the shape extraction part, one of the current major problems is that some annotations may lay on top of the building boundary. Then after shape extraction, the retrieved building shape will be distorted. In Figure 12, the block number is overlapped with the building boundary of Block No.243. Figure 13 shows the failure case of extracting its shape. We plan to add post-processing to refine the extracted shape for such a situation. Also, even though the maximum zoom level of the new OneMap Static Map API is used for generating the image to be processed, its resolution is still a bit too low, so some artifacts may be introduced along the building boundary. We intend to add image super resolution or vectorization parts to overcome this problem.

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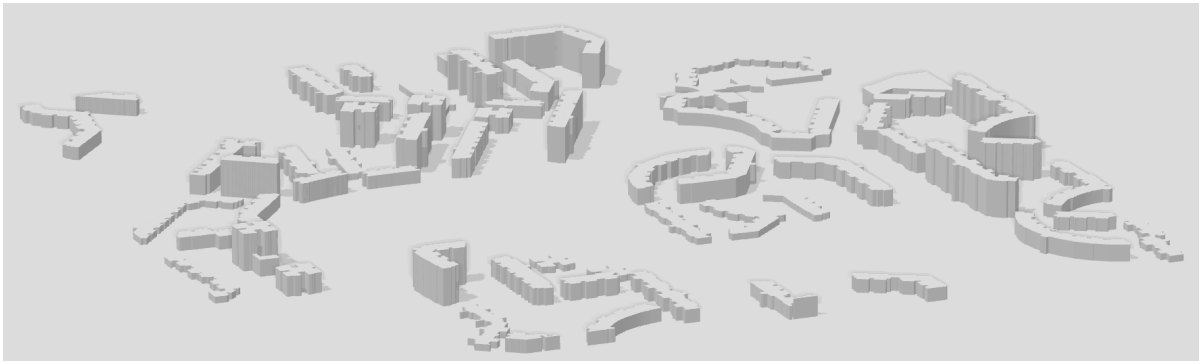

Figure 10: A view of 3D models of all target buildings from the neighborhood in Figure 8.

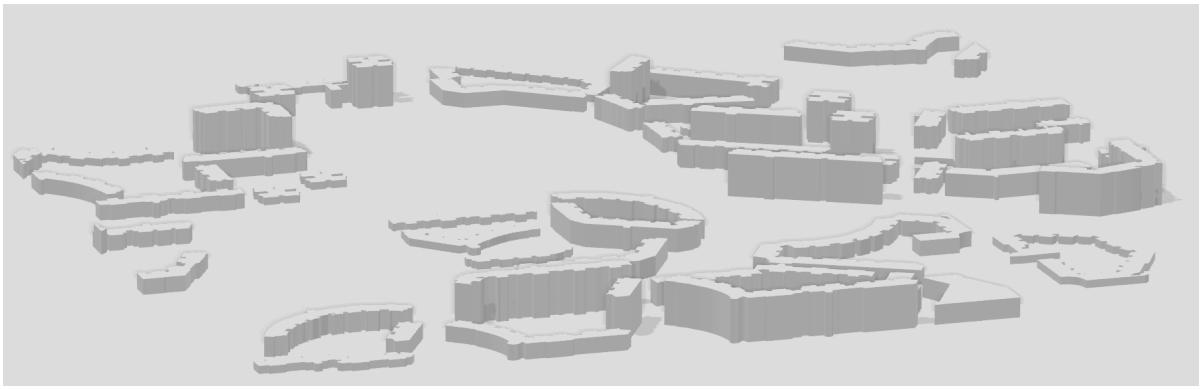

Figure 11: Another view of 3D models of all target buildings from the neighborhood in Figure 8.

Figure 12: Image retrieved with annotation on top of target building (Block No.243) boundary.(NewOneMap, 2018)

Figure 13: Extraction of distorted target building shape.

REFERENCES

Ahmed, S., Liwicki, M., Weber, M., and Dengel, A. (2011). Improved automatic analysis of architectural floor plans. In *2011 International Conference on Document Analysis and Recognition*, pages 864–869.

Ahmed, S., Liwicki, M., Weber, M., and Dengel, A. (2012). Automatic room detection and room labeling from architectural floor plans. In *2012 10th IAPR International Workshop on Document Analysis Systems*, pages 339–343.

Bartz, C., Yang, H., and Meinel, C. (2017a). See: Towards semi-supervised end-to-end scene text recognition. *arXiv preprint arXiv:1712.05404*.

Bartz, C., Yang, H., and Meinel, C. (2017b). STN-OCR: A single neural network for text detection and text recognition. *CoRR*, abs/1707.08831.

Biljecki, F., Ledoux, H., and Stoter, J. (2016). An improved LOD specification for 3D building models. *Computers, Environment and Urban Systems*, 59:25–37.

Biljecki, F., Ledoux, H., and Stoter, J. (2017). Generating 3D city models without elevation data. *Computers, Environment and Urban Systems*, 64:1–18.

Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.

Breuel, T. M. (2008). The OCRopus open source OCR system.

Epshtein, B., Ofek, E., and Wexler, Y. (2010). Detecting text in natural scenes with stroke width transform. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 2963–2970. IEEE.

Fritsch, D. and Klein, M. (2018). 3D preservation of buildings – reconstructing the past. *Multimedia Tools and Applications*, 77(7):9153–9170.

Gröger, G., Kolbe, T., Nagel, C., and Häfele, K. (2012). OGC city geography markup language (CityGML) encoding standard, version 2.0, ogc doc no. 12-019. *Open Geospatial Consortium*.

Jaderberg, M., Simonyan, K., Vedaldi, A., and Zisserman, A. (2016). Reading text in the wild with convolutional

neural networks. *International Journal of Computer Vision*, 116(1):1–20.

Liu, X., Liang, D., Yan, S., Chen, D., Qiao, Y., and Yan, J. (2018). FOTS: Fast oriented text spotting with a unified network. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5676–5685.

Matas, J., Chum, O., Urban, M., and Pajdla, T. (2002). Robust wide baseline stereo from maximally stable extremal regions. In *Proceedings of the British Machine Vision Conference*, pages 36.1–36.10. BMVA Press. doi:10.5244/C.16.36.

Neumann, L. and Matas, J. (2010). A method for text localization and recognition in real-world images. In *Asian Conference on Computer Vision*, pages 770–783. Springer.

Neumann, L. and Matas, J. (2012). Real-time scene text localization and recognition. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 3538–3545. IEEE.

NewOneMap (2018). New OneMap Search API, `https://docs.onemap.sg/#search`. New OneMap Static Map API, `https://docs.onemap.sg/#static-map` Contains information from new OneMap accessed on 13th November 2018 from new OneMap Static Map API, which is made available under the terms of the Singapore Open Data Licence version 1.0: `https://www.onemap.sg/legal/opendatalicence.html`.

Shi, B., Bai, X., and Yao, C. (2015). An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *CoRR*, abs/1507.05717.

Simonyan, K. and Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556.

Smith, R. (2007). An overview of the tesseract OCR engine. In *Proceedings of the Ninth International Conference on Document Analysis and Recognition - Volume 02*, ICDAR '07, pages 629–633, Washington, DC, USA. IEEE Computer Society.

Soille, P. (2002). On morphological operators based on rank filters. *Pattern Recognition*, 35(2):527 – 535.

Sugihara, K., Murase, T., and Zhou, X. (2015). Automatic generation of 3D building models from building polygons on digital maps. In *2015 International Conference on 3D Imaging (IC3D)*, pages 1–9.

Ye, Q. and Doermann, D. (2015). Text detection and recognition in imagery: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(7):1480–1500.

Zhou, X., Yao, C., Wen, H., Wang, Y., Zhou, S., He, W., and Liang, J. (2017). EAST: an efficient and accurate scene text detector. *CoRR*, abs/1704.03155.

Zhu, Y., Yao, C., and Bai, X. (2016). Scene text detection and recognition: Recent advances and future trends. *Frontiers of Computer Science*, 10(1):19–36.