Contour detection

Fabien Lagnieu, Maha Kadraoui, Tristan Waddington, Abdoul Zeba
Mentor: Stéphane Maviel (CEO Vinci/Diane[1])

Architects are drawing floor plans using a Computer-Aided Design (CAD) software. These files are used by engineers to plan and conduct the construction of the building. In this process, additional measures are needed such as the room size or adjacency. **The goal of this project is to develop a tool that can automatically detect the contours of the rooms in the floor plan to draw it back into the CAD software.**

1 Context

Vinci's engineers are dealing with a different floor plan for every project they are working on. Every plan has its own drawing style and the contours of the rooms are often mixed with other lines, but they need this information to plan the location of smoke detectors, fire extinguishers, and other facilities in the building. The goal of this project is to develop a tool that can automatically detect the contours of the rooms in the floor plan and draw back the polygons in the CAD software as a vector layer for further automatic processing. Diane's teams have already worked on this problem and developed a first version of the tool that is too slow and not accurate enough. They are looking for other approaches to improve it.

Datasets We are given examples of GeoJSON[2] exports of CAD plans. The first dataset is composed of 9 GeoJSON exports of floor plans from very different buildings (datacenter, hospital, office...). Each file contains a list of points connected together to form lines or polygons representing walls, windows, doors, or furniture.

The second dataset export the floor plans of 5 whole buildings in the same format as the previous one. Each plan is joined by a second file containing the actual contours of the rooms as a target. This dataset is really useful to compute metrics of our models.

2 Methods

After a first phase of data cleaning we focus on two different paths to solve the problem:

1. **Geometric process** Transform the geometries into normalized segments [4] then cluster the lines to create the polygons[1] of the contours. This path relies on the geometric libraries `shapely` and `geopandas`. The graph representation was later discarded as too computational expensive.

2. **Image segmentation** Using a dense literature review[3], we spot some successful uses of CNNs[5]. This same paper also provides the list of datasets of floor plans as images we can use for training deep learning models. Ultimately, this path gives us the idea of the segmentation of the floor plans into rooms, using basic computer vision methods and the Segment Anything Model (SAM)[2].

[1]Diane is Vinci's inside Startup tasked to find numerical solutions to ease the work of Vinci collaborators.
[2]The current standard for GeoJSON format was published in August 2016 by the Internet Engineering Task Force (IETF), in RFC 7946.

At the end of our research, we produce 3 models of different complexity ranging from geometric hand-crafted rules to fully automatic computer vision: `SegmentBasedClustering`, `VisionSegmentation`, and `SegmentAnythingModel`. They share common steps and a global representation is given in figure 1. The individual pipelines are detailed in the following sections.

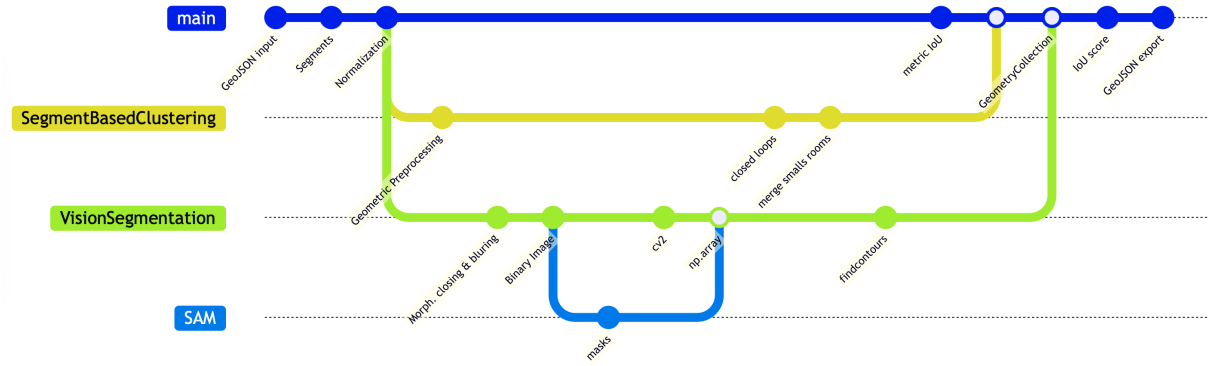

Figure 1: Articulation of the shared steps of the three models.

2.1 Geometric Preprocess

Before feeding GeoJSON files into the model, a preprocessing step is applied to clean and standardize the segment data. This ensures accurate room segmentation while minimizing errors caused by noise, misaligned geometries and above all, plans drawn with different scales.

Preprocessing Steps The preprocessing consists of five successive steps: (i) **Splitting into segments** the complex geometries. (ii) **Normalizing segments** by sorting segment endpoints to avoid duplicate representations and rescaling to the meter unit. (iii) **Snapping** close endpoints by aligning nearby segment endpoints (within 0.05m) for better connectivity. (iv) **Removing isolated** segments by eliminating segments not connected to any others. (v) **Merging collinear** segments by combining nearly aligned segments to reduce fragmentation.

The preprocessing significantly reduces the number of segments (up to 70%) while preserving the overall geometry. See figure 6 for visual results. Additional details and tables can be found on appendix A.

2.2 Model 1: `SegmentBasedClustering`, Based On Geometric Rules

This model is a geometric rule-based method designed to extract room boundaries from architectural floor plans provided in GeoJSON format. This method leverages classic computational geometry techniques to detect closed paths and segment parts based on structural constraints. It does not require training data. Further details and pipeline description can be found in appendix B.

Discussion `SegmentBasedClustering` offers an efficient approach to segmenting rooms in architectural plans without resorting to complex models nor heavy computing resources. By leveraging topological and geometric operations, the method ensures robust room segmentation. However, this approach needs explicit physical separations between rooms. If there are no walls or voids, inconsistent results may be obtained.

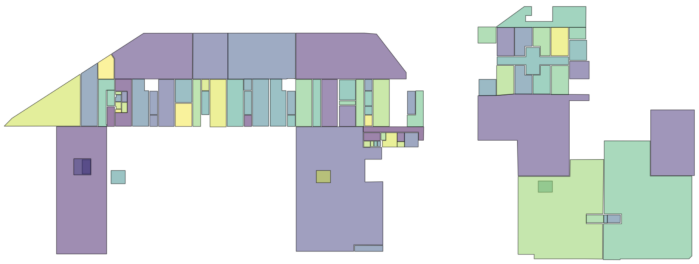

Figure 2: Example of rooms detections using `SegmentBasedClustering`.

2.3 Model 2: VisionSegmentation, Based On Computer Vision

The other rule-based method leverages classical computer vision techniques to extract room boundaries from geometric data, without requiring training datasets.

The pipeline consists of converting vector data into raster images, applying image processing operations to detect closed areas, and exporting the resulting room contours back into a geo-referenced vector format (GeoJSON). The entire workflow is based on `OpenCV` image processing primitives and geospatial data transformations from `shapely`. Further details and pipeline description can be found in appendix C.

Figure 3: Example of rooms detections using `VisionSegmentation`. Left: Binary image generated from vector segments. Right: Colorized visualization of detected rooms. Room without doors are merged in this version.

Discussion This vision model offers a simple yet robust solution for room segmentation on vector floor plans. It avoids the complexity of enforcing strict topological rules in vector space and instead leverages the flexibility of raster-based computer vision techniques. The method is particularly suited to noisy, exports where traditional vector-based approaches may struggle.

However, the `VisionSegmentation` also depends on the explicit representation of physical separations. In cases where doors are missing, or open connections are not physically modeled, adjacent spaces may be incorrectly merged into a single room.

2.4 Model 3: SAM, Based on Segment Anything

To handle the open door issue, we explore an other vision-based model based on the Segment Anything Model (SAM)[2]. SAM is a foundation model for image and videos segmentation. Devel-

oped by Meta's FAIR (Fundamental AI Research) lab, SAM represents a significant advancement in computer vision, designed to serve as a versatile framework for various segmentation tasks. His architecture can be summarized in three parts: a Vision transformer image encoder, a prompt encoder, and a modified mask Transformer decoder block (see Figure 4, taken from original paper [2]). Further details and pipeline description can be found in appendix D.

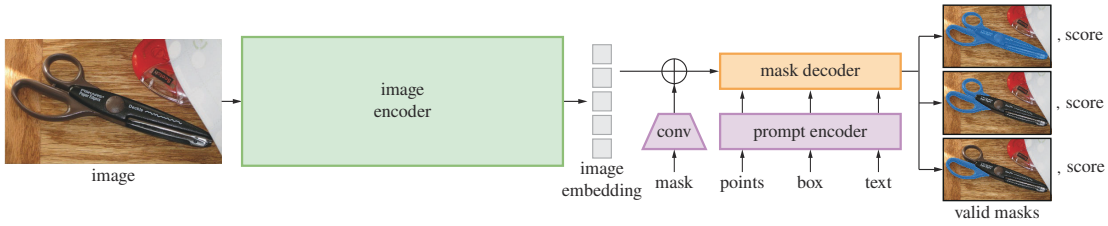

Figure 4: Segment Anything Model (SAM) overview

Discussion This model is way more computationally expensive than the two previous ones, and requires GPU memory to detect rooms in seconds. It correctly splits the non-connected rooms and is able to detect rooms without doors. However, the model is not as precise as the other ones.

3 Results

3.1 The metric to use

Text of the subsection.

3.2 The results

Figure 5: Example of the results obtained with image segmentation, each room should be in a different color.

4 Conclusion

Summarize and discuss the main findings. What are the limitations?
Are the experiments conclusive? With more time, what else would you have tried?

Organization within the team The project initially started in the office of Vinci/Diane for a brainstorming session. Since then, we have been working remotely in a smooth way, meeting with Vinci/Diane at the beginning of each Thursday afternoon. We were using a shared git repository to share our code and results[3].

Tristan took care of the global information management process and organized the relations with Vinci. After a first quick diverging phase where every one has tried different methods and dug into the data, we have split in teams of two to focus on two paths described in section 2.

- Tristan handled the initial data cleaning, then worked with Maha who expertly created the geometric process and the segment preprocessing and clustering.
- Abdoul explored first the computer vision path and Fabien made the breakthrough in the results with the image segmentation.

References

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[2] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollár, and Ross Girshick. Segment anything, 2023.

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[4] Martin Schafer, Christian Knapp, and Samarjit Chakraborty. Automatic generation of topological indoor maps for real-time map-based localization and tracking. *2011 International Conference on Indoor Positioning and Indoor Navigation*, pages 1–8, 2011.

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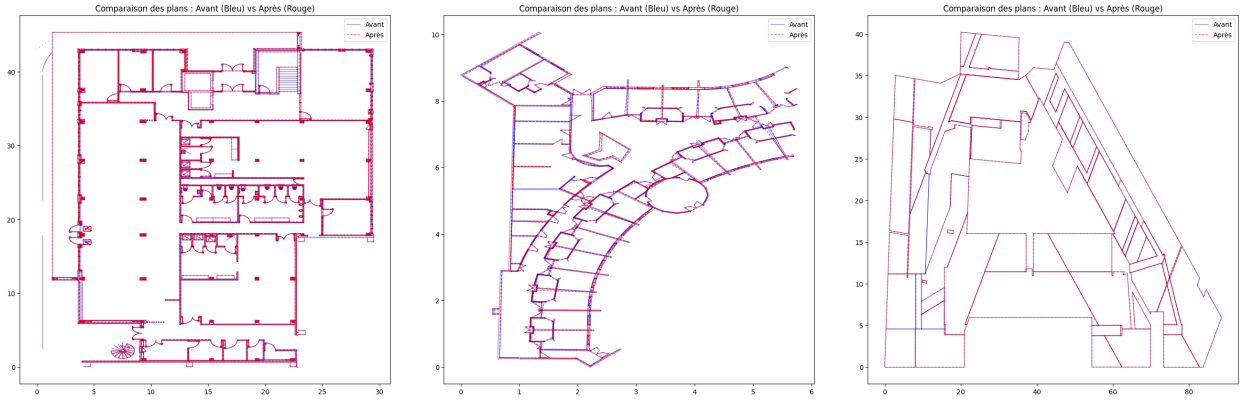
[3] Private: https://github.com/waddason/CapstoneContour

A Additional details on the geometric preprocessing

Preprocessing Results This preprocessing step is particularly effective for large datasets with high redundancy, as it reduces computation complexity while maintaining architectural integrity. But it can be problematic when applied to smaller input datasets like in our third example. So it should be used with caution, as excessive modification of small datasets can worsen distortions, as seen with 520 segments where a 0.443m displacement occurred. As a consequence, the preprocessing step is an option when using our models.



Case1: output2 Case2: output7 Case3: output3

Figure 6: Comparison of floor plans before (Blue) and after (Red) preprocessing for 3 different test cases. The near absence of blue segments proves that we have removed a lot of noise.

The following tables summarize the impact of the geometric preprocessing on the segment count and the average displacement after preprocessing. We used three different floor plans that spans along the range of complexity of the dataset.

The drop in segment count is significant, with a reduction of over 70% in most cases, reducing computational cost of the ulterior tasks. See table 1 for details.

Test Case	Nb segments before	Nb segmetns after	Reduction %
Case 1	22,425	6,417	71.38%
Case 2	6,013	1,648	72.59%
Case 3	520	330	36.54%

Table 1: Impact of geometric preprocessing on segment count.

This drop in segment count comes with a light cost in the accuracy of the representation. On most cases, the segments are moved of about 2 cm, which is acceptable for the purpose of the project. See table 2 for details.

Test Case	Avg. Displacement
Case 1	0.02
Case 2	0.025
Case 3	0.443

Table 2: Average displacement after preprocessing.

In our code, this preprocessing is the method `preprocess_segments.complete_preprocessing( segments, angle_tol=0.1, distance_tol=0.3, snap_tol=0.05) -> cleaned_segments`. Where `angle_tol` is the maximum angle between two segments to be considered collinear, `distance_tol` is the maximum distance between two segments to be considered collinear, and `snap_tol` is the maximum distance between two endpoints to be snapped together.

B Additional details about SegmentBasedClustering model

Pipeline Description The pipeline follows a sequence of geometric operations performed using the `Shapely` computational geometry library.

1. Extracting relevant **wall segments** from GeoJSON data.
2. Identifing **closed loops** using geometric operations.
3. Retaining valid rooms based on predefined **area constraints**, considering only polygons between 1 m^2 and 1000 m^2 (hyperparameters).
4. Identifing which rooms share **common boundaries** by doing adjacency analysis to facilitate merging and spatial organization.
5. **Combining and merges small rooms** (under 5 m^2) with their largest adjacent neighbor.

C Additional details about ComputerVision model

Pipeline Description The method is structured in the following key steps:

1. **Vector Preprocessing.** Raw GeoJSON data often includes heterogeneous geometries (Polygons, MultiPolygons, LineStrings), many of which are noisy or incomplete. We filter the data to retain only the linear primitives representing walls. The geometries are rescaled and recentered to ensure consistent metric resolution before conversion. This corresponds to the steps (i) and (ii) described in the geometric preprocessing in section 2.1.
2. **Binary Image Generation.** The preprocessed segments are rasterized into binary black-and-white images, where each segment is drawn with a configurable thickness (default: 3 pixels). A DPI value of 50 (pixels per meter) ensures sufficient spatial resolution. To improve the connectivity of wall segments, we apply Gaussian dilation, which smooths the edges and *ensures continuity* even in curved or oblique wall segments. Result is shown on figure 3 left.
3. **Morphological Processing and Contour Detection.** A morphological closing operation (`cv2.morphologyEx` with `MORPH_CLOSE` operation) fills small gaps between wall segments. Contours are then extracted with `cv2.findContours` using the `RETR_CCOMP` mode, producing a hierarchical tree structure that allows holes (e.g., internal courtyards or voids) to be identified and processed correctly.
4. **Wall Filtering and Room Selection.** To discriminate between rooms and walls, we apply geometric criteria. Only contours with a surface area greater than 1 m^2 (2500 pixels at 50 DPI) and an average thickness (surface-to-perimeter ratio) exceeding 0.4 meters are retained. Best parameters displayed in table 3 have been found using the validation dataset.

   Additionally, the longest contour—typically representing the building envelope—is discarded. The detected rooms are shown on figure 3 right.
5. **Polygon Conversion and GeoJSON Export.** The valid contours are converted back into metric coordinates using transformation parameters from the rasterization step. Polygons are enriched with properties such as area (m^2) and a unique room identifier. Final outputs are exported in GeoJSON format to be loaded back into CAD software.

DPI	50 pixels per meter (1 pixel ≈ 2 cm)
Wall thickness	3 pixels (default)
Minimum room area	1 m^2
Minimum average thickness	0.4 m
Dilation method	Gaussian

Table 3: Best `VisionSegmentation` Model Parameters

D Additional details about SAM model

Pipeline Description We first produce a high-quality image using the two first steps of the `VisionSegmentation` pipeline presented earlier. Then, we use SAM to infer masks on the image as segmentation of all the rooms. Finally, the contours of the masks are extracted, and after rescaling the contour coordinates, we generate the corresponding GeoJSON file. The SAM checkpoint used is described in table 4.

Checkpoint	`sam_vit_h_4b8939.pth`
Backbone Size	Huge (ViT-H)
Model Parameters	636 million
File Size	2.4 GB
GPU Memory Requirement	At least 8 GB
Use Case	Tasks requiring high-quality segmentations

Table 4: `SAM` Model Checkpoint Information