Automated Indoor Pedestrian Networks Reconstruction from As-Built Floorplan Drawings using LLM and YOLO

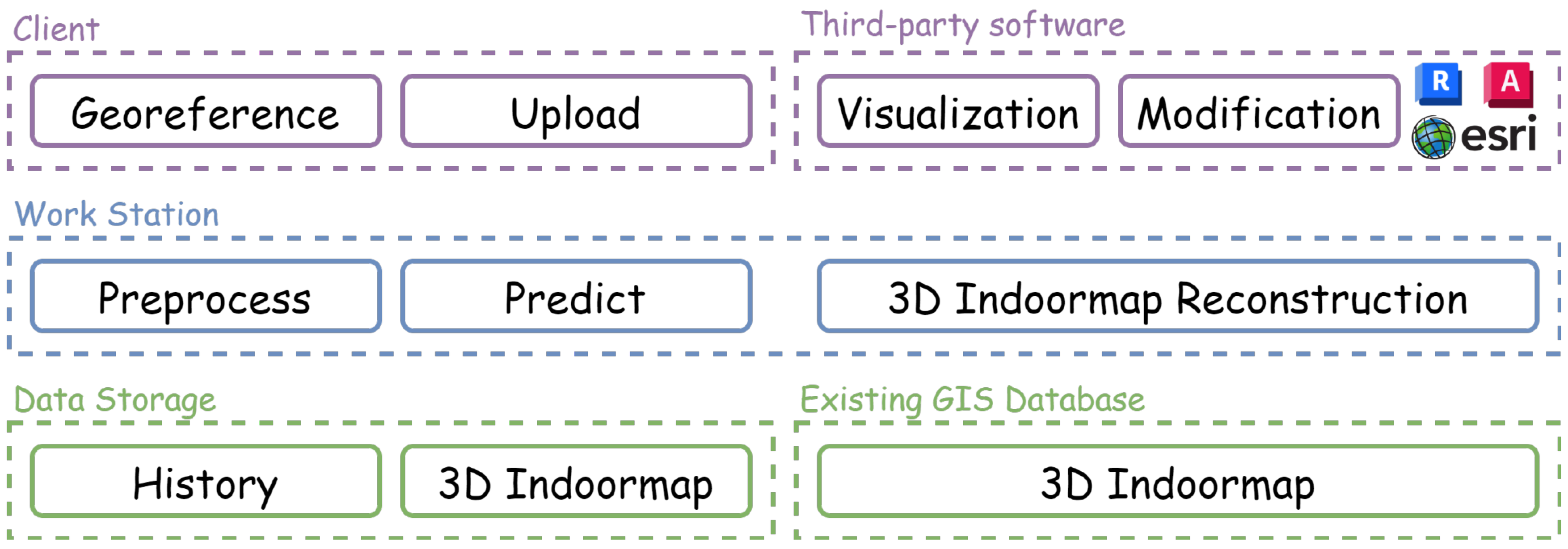
Longyong Wu, Fan Xue

Department of Real Estate and Construction Management, The University of Hong Kong, Hong Kong, China

Introduction

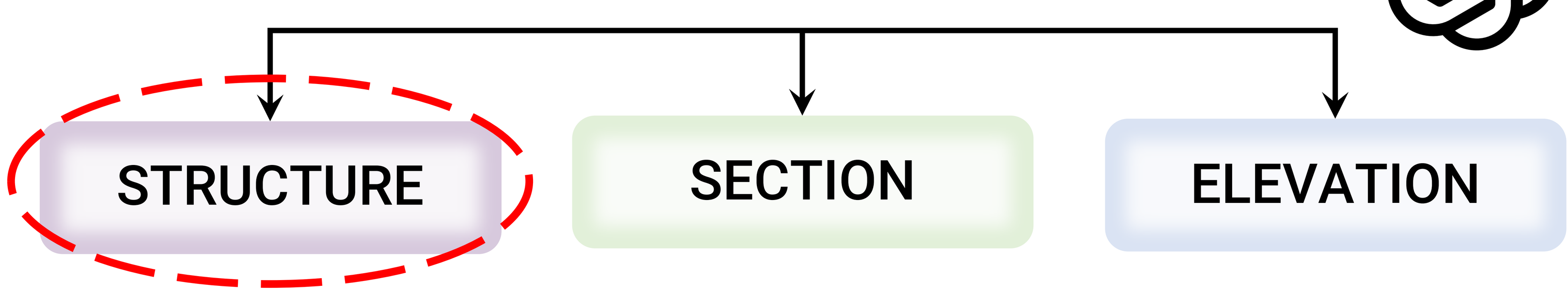
Pedestrian networks play a crucial role in pedestrian navigation. However conventional 3D indoor mapping methods for reconstructing indoor networks are costly, involving intensive labor work and expensive equipment. This paper proposes an automated pipeline to reconstruct pedestrian networks from 2D as-built floorplan drawings (or 3D BIMs). Pilot tests on the real-world drawings in Hong Kong proved the pipeline achieved accurate indoor space detection (mIoU =87.24%) by retraining YOLO.

Methods



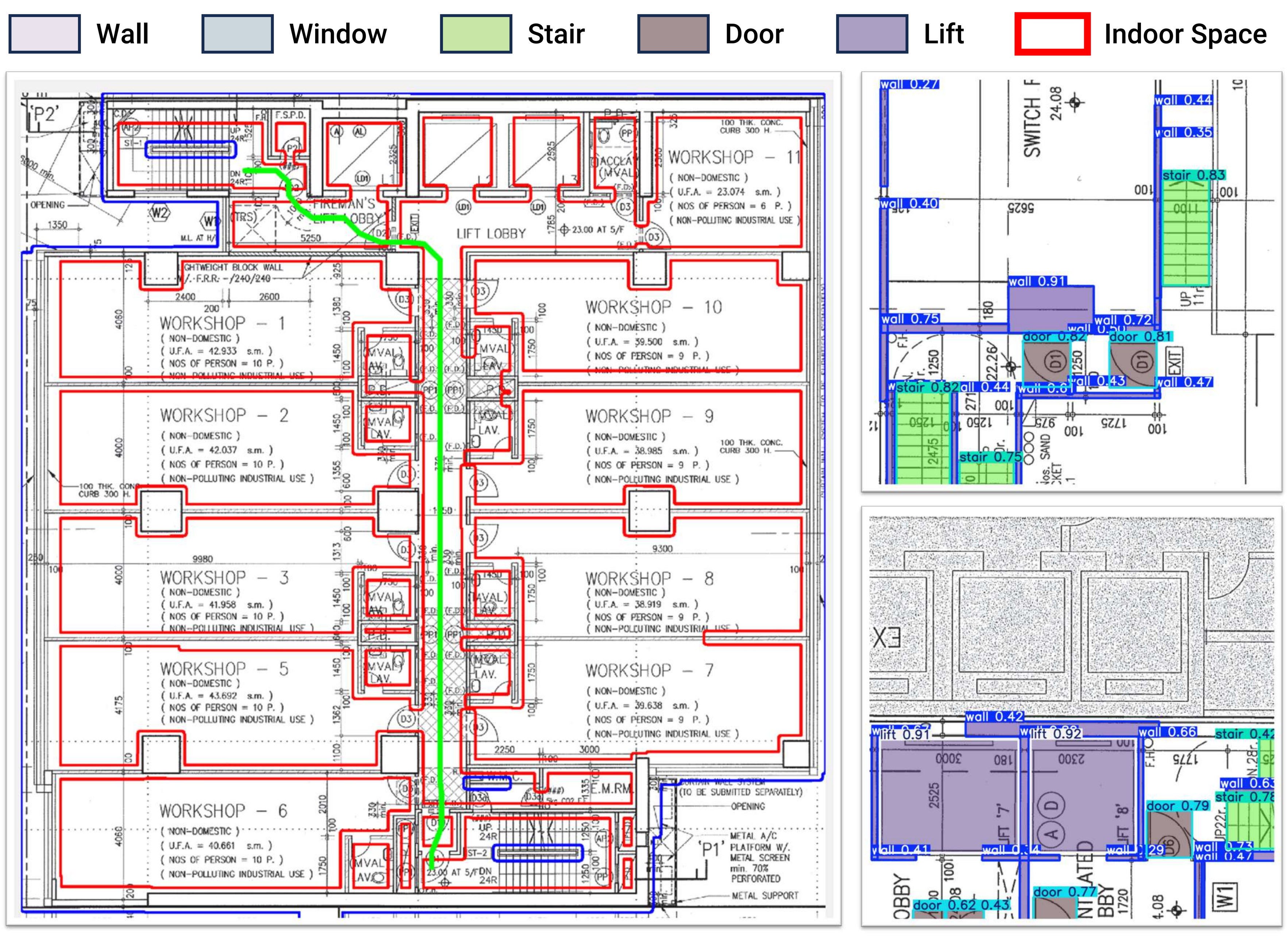
1. At the Client layer, users interact with the system through third-party software like Revit, AutoCAD, or ArcGIS Pro.
2. The Server layer handles compute-intensive tasks using graphics processing units (GPUs).
3. The Data Storage layer stores reconstruction histories, the resulting 3D indoor maps, and other related information.

STEP 1: Drawings Classification



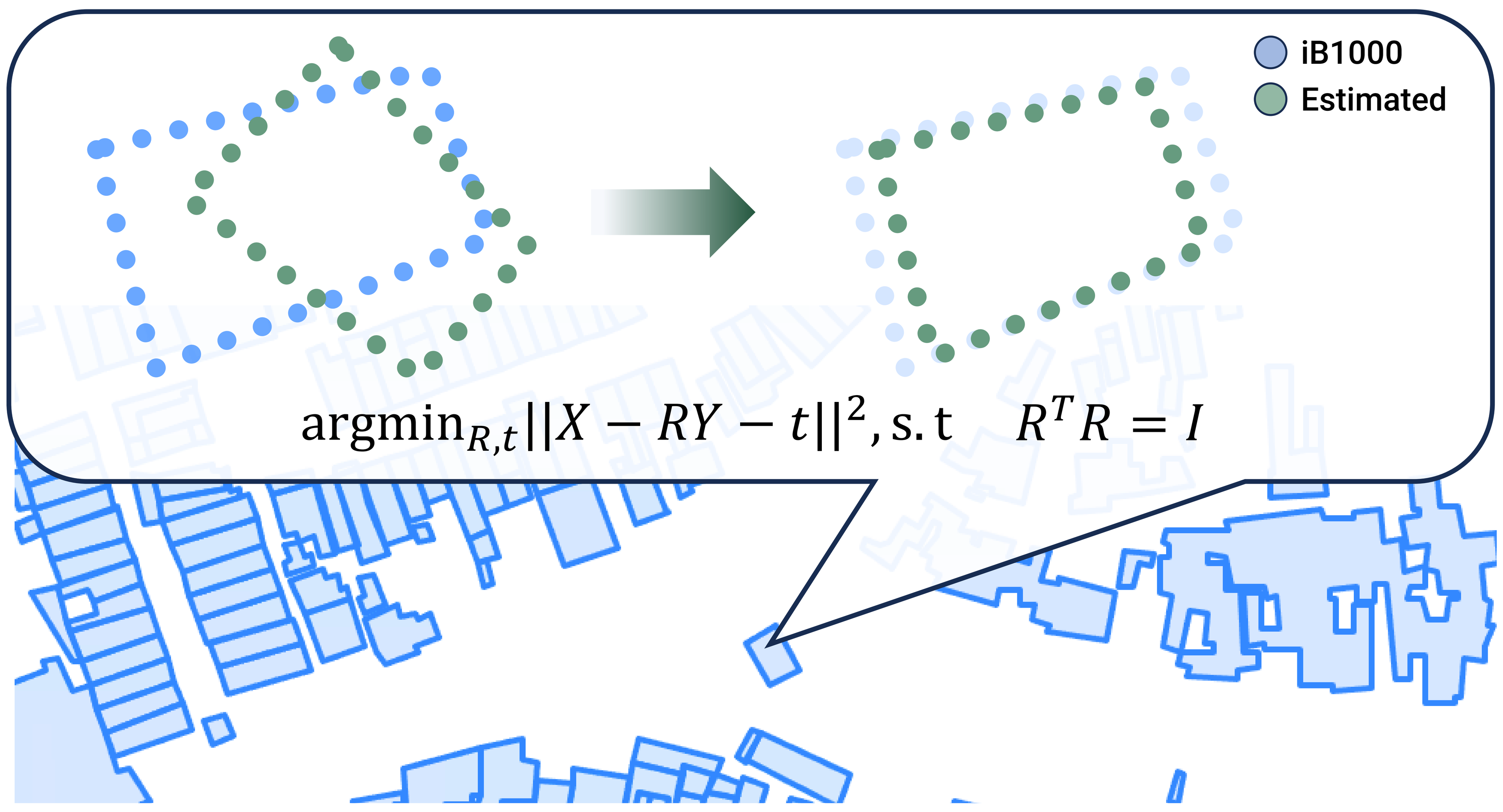
1. Streamline the data formats of 2D vector drawings or 3D BIMs as high-resolution 2D raster images
2. Classify each image into different categories using a Large Language Model (LLM) , ChatGPT 4o [1].

STEP 2: Structural Elements Detection



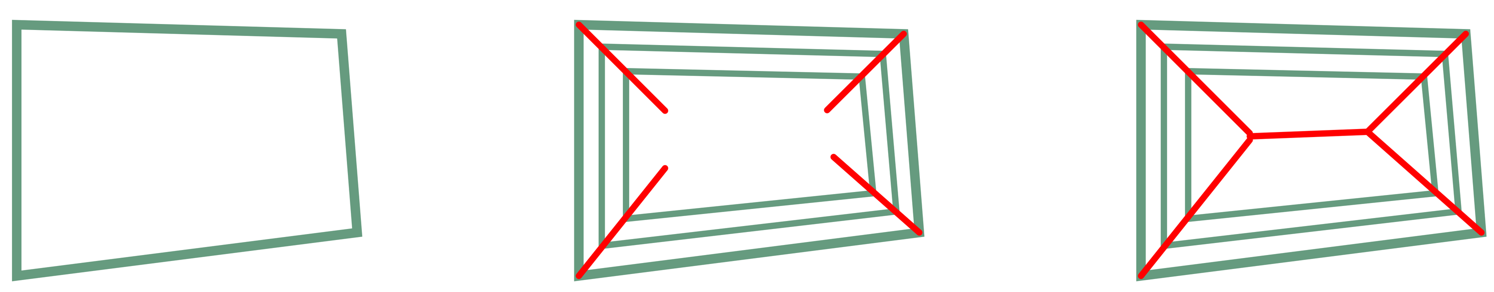
Retrain the YOLO (V8) [2], a well-known pre-trained deep model for 2D object detection, to detect key structural elements, such as walls, doors, openings, staircases, and elevators, from the images of structural floorplans.

STEP 3: Geo-referenced Coordinates Assignment [3]



$$\text{argmin}_{R,t}||X - RY - t||^2, \text{s.t} \quad R^T R = I$$

STEP 4: Pedestrian Networks Creation



Create indoor pedestrian networks from simplified skeletons of room spaces against fixed points of structural elements [4].

Results

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

1. Type: Raster (made after Year 2000)
2. Processing time: 25.77s (predict) + 128.57s (post-process) + 3.51s (map + path)
3. Indoor Space IoU (Intersection over Union): 87.24%

Conclusion

The findings of this paper demonstrate that the automated pipeline, taking advantage of the power of LLM and retraining a well-known deep learning model, is efficient and cost-effective for multidimensional information extraction and precision mapping, supporting smart city development in Hong Kong and beyond.

Acknowledgment

Thanks to Miss Vanessa and Mr. Alvin from Survey and Mapping Office for the data.

References

[1] GPT-4o. https://openai.com/index/hello-gpt-4o/
[2] Jocher, G., Qiu, J., & Chaurasia, A. (2023). Ultralytics YOLO (Version 8.0.0) [Computer software]. https://github.com/ultralytics/ultralytics
[3] Myronenko, A., & Song, X. (2010). Point set registration: Coherent point drift. IEEE transactions on pattern analysis and machine intelligence, 32(12), 2262-2275.
[4] CGAL, Computational Geometry Algorithms Library, https://www.cgal.org