# Extraction and Merging of Topometric Maps of Indoor Environments

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- 3D maps of indoor environments are useful
  - Cartography for human understanding (Chen & Clarke, 2020)
  - Automated robot understanding (Wang et al, 2019)

- Even moreso when created collaboratively (Schuster et al, 2020)

- How do we create a map together?
  - **No** GNSS because indoors
  - **No** indoor positioning systems
  - **No** knowledge of each other

- The answer is **map merging**

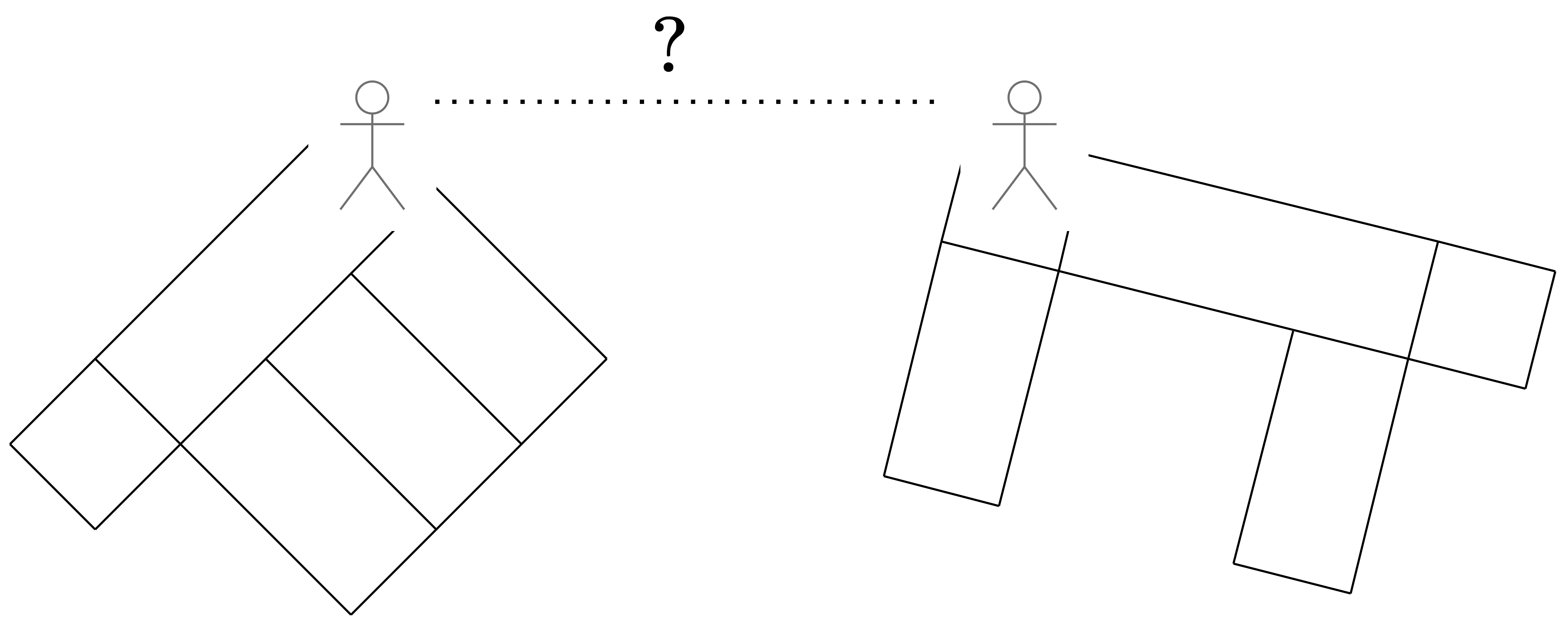


Figure 1: *Illustration of map merging problem in indoor environments (van Schendel, 2022)*

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- Combine multiple partial maps into a global map

- Two subproblems
  - **Map matching** identifying overlapping areas
  - **Map fusion** combining partial maps based on overlap

- Why is it hard?
  - Partial maps have unknown relative positions and orientations.
  - Partial maps may be incomplete
  - Partial maps may be different

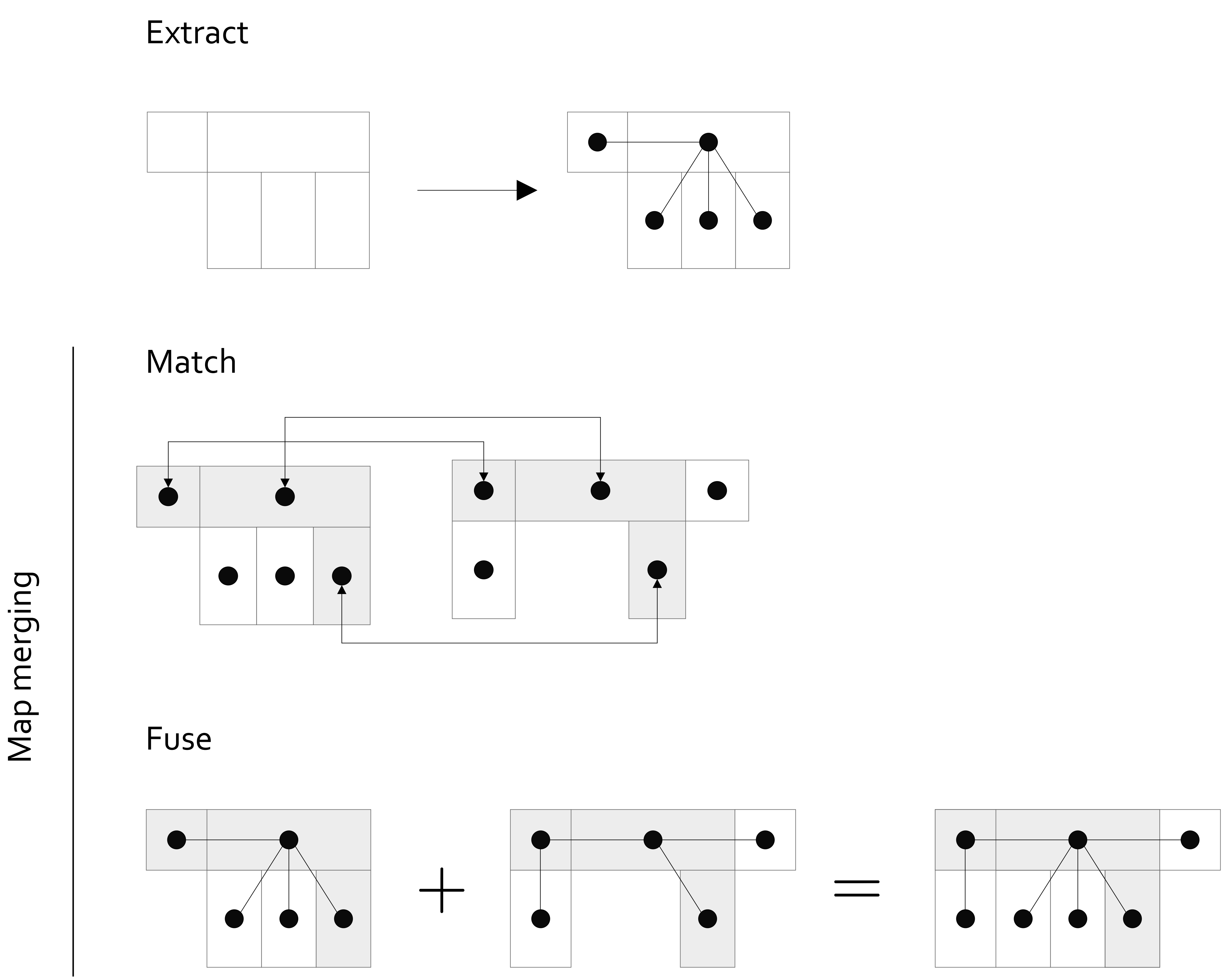


Figure 2: *The three subproblems of this thesis (van Schendel, 2022)*

- Can we apply human understanding of place to map merging?

- Both metric and topological characteristics (Kuipers, 1978)

- Map containing both: topometric map

- **Hypothesis**: use topometric maps to solve map merging problem.

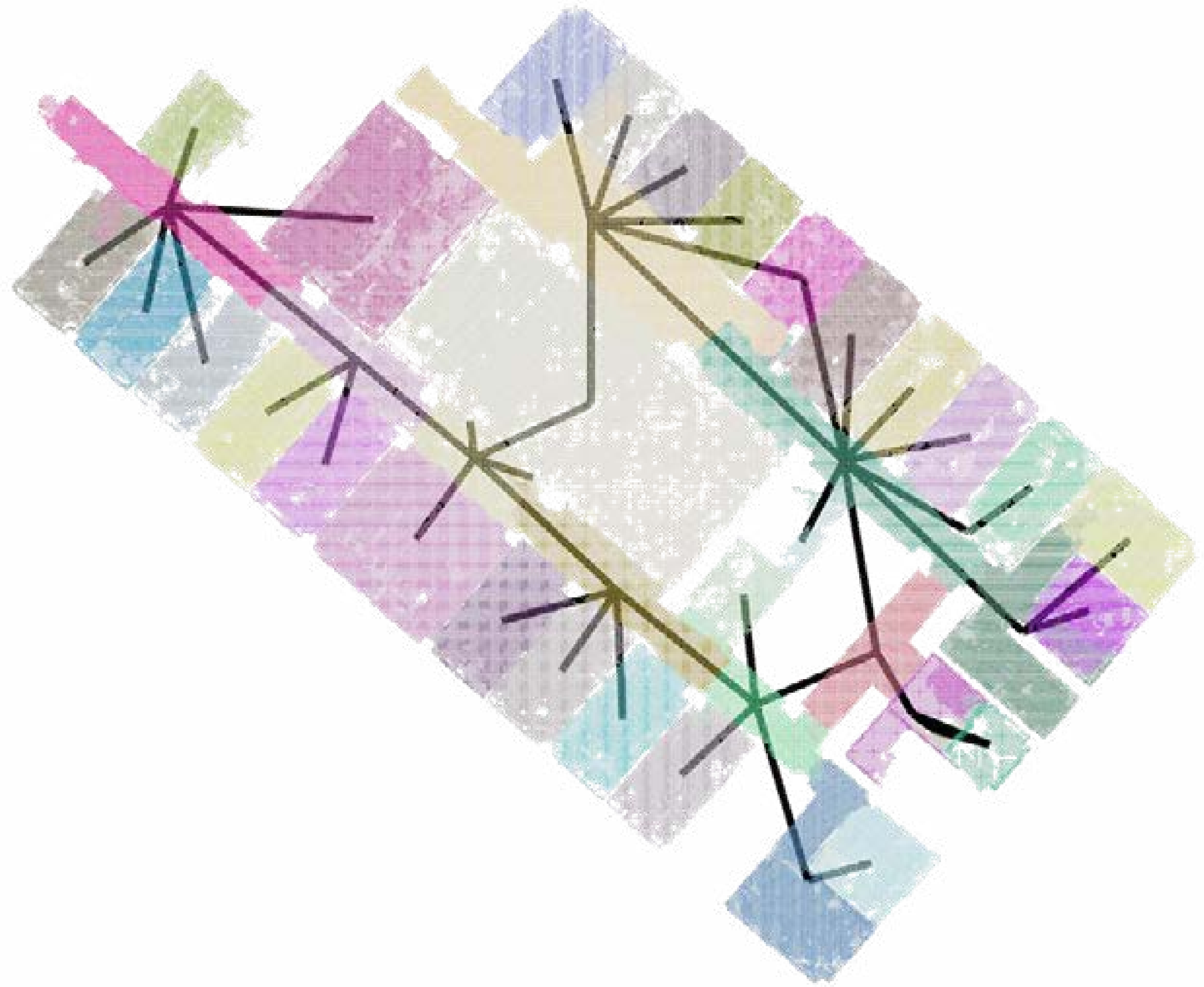

Figure 3: *Example of a topometric map (van Schendel, 2022)*

- Main research question

*How can we apply topometric representations of indoor environments to solve the map merging problem?*

- Sub-questions

*In what way can partial topometric maps be extracted from partial point cloud maps?*

*What approach is best suited for identifying matches between partial topometric maps?*

*How can the identified matches be used to fuse two or more partial topometric maps into a global topometric map?*

- Three-step methodology

- Map extraction / map matching / map fusion

- **Input** two partial point cloud maps
  **Output** one global topometric map

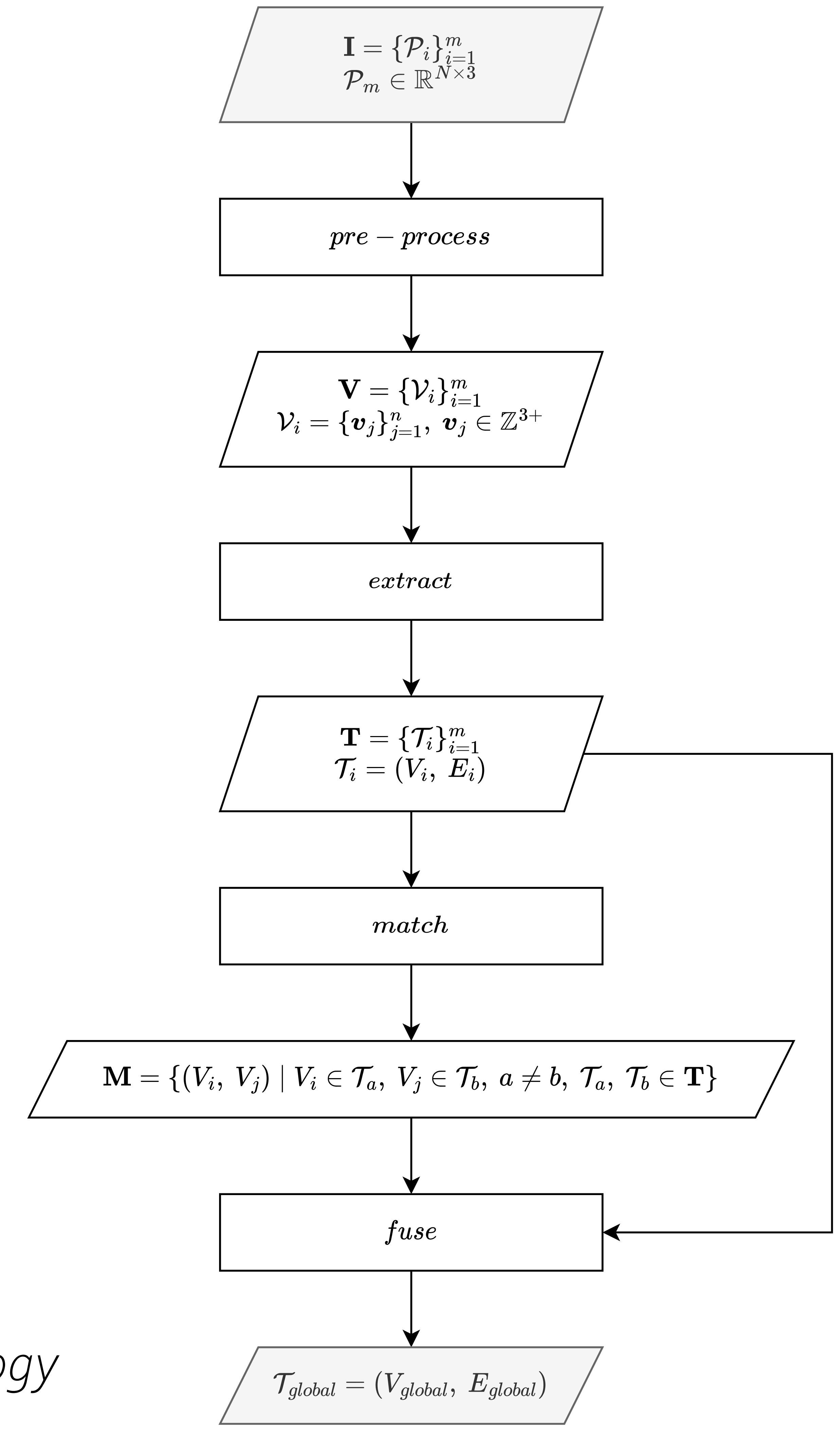


Figure 4: *overview of methodology (van Schendel, 2022)*

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- Represents navigability relationships between distinctive places

- Two places adjacent if a human can move between them without passing through another place

- Place is a subjective concept, here refers to rooms

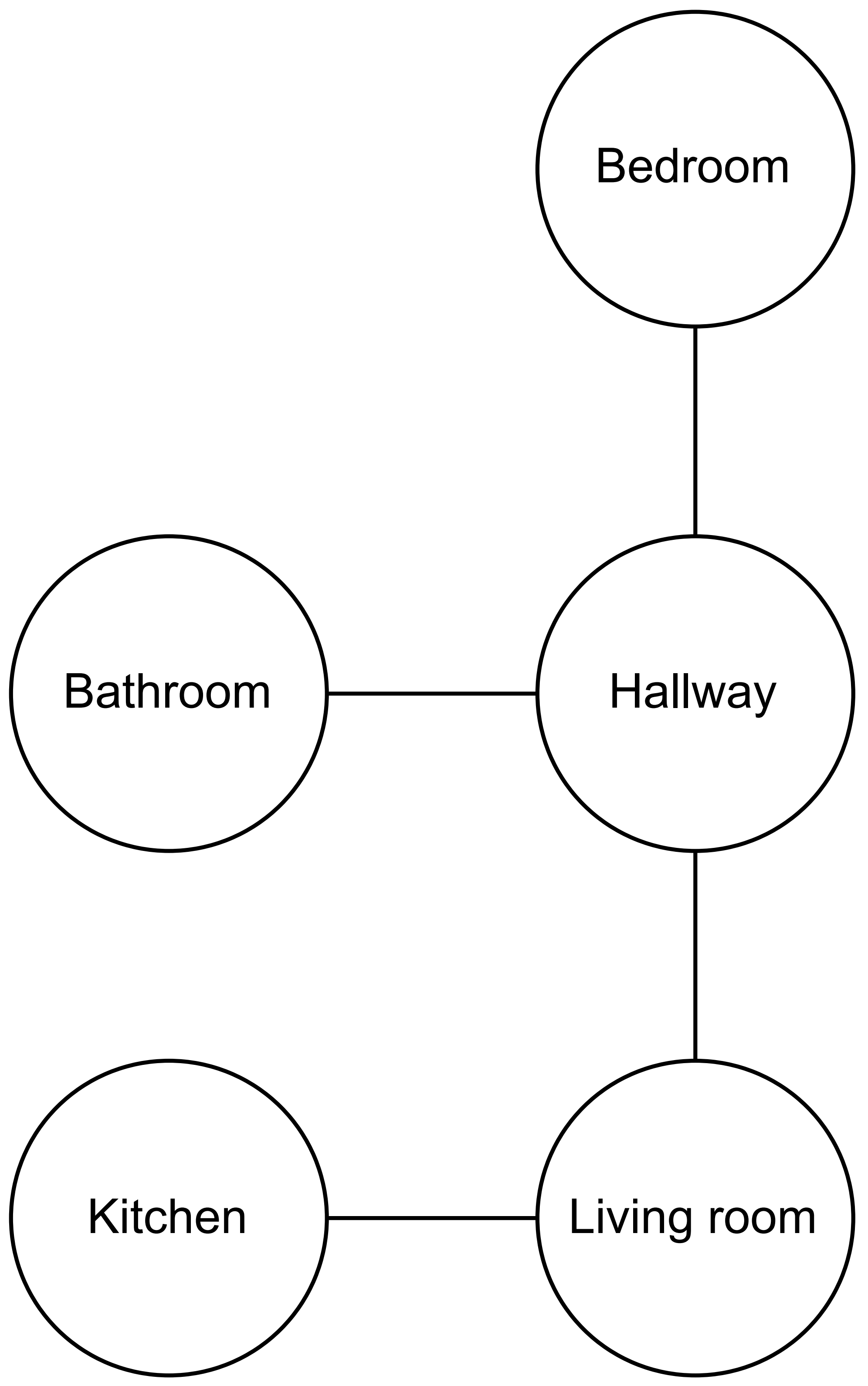


Figure 6: *Example topological map of an indoor environment (van Schendel, 2022)*

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- Represents geometry as grid of cubic cells
- Voxel convolution
- Neighbourhood graph

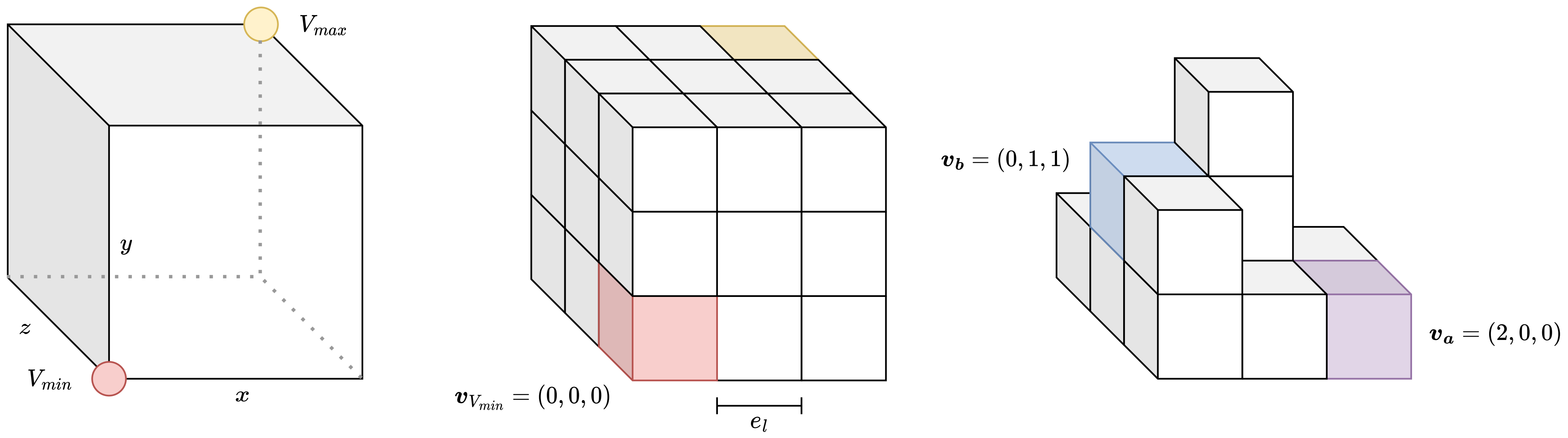


Figure 7: *The basic components of a voxel grid (van Schendel, 2022)*

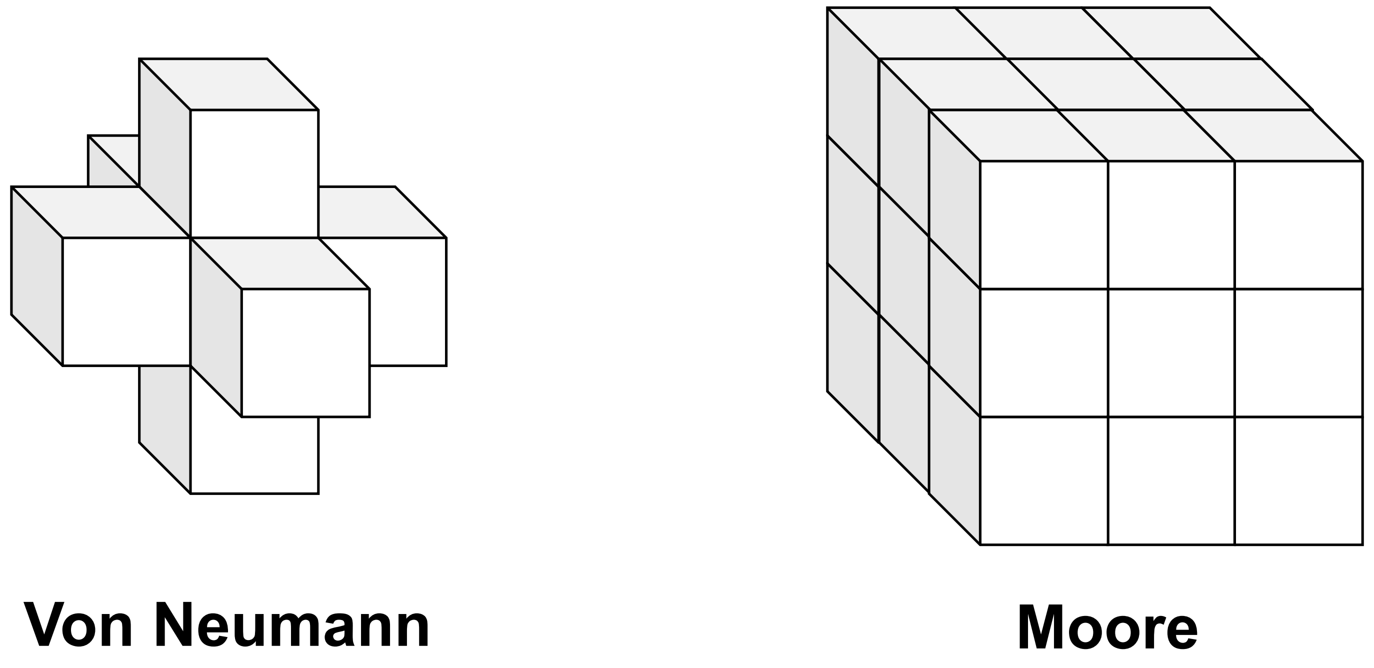


Figure 8: *Two common kernels used for constructing a neighbourhood graph (van Schendel, 2022)*

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- Hybrid representation inspired by human spatial understanding

- Topological graph

- Metric (voxel grid) nodes

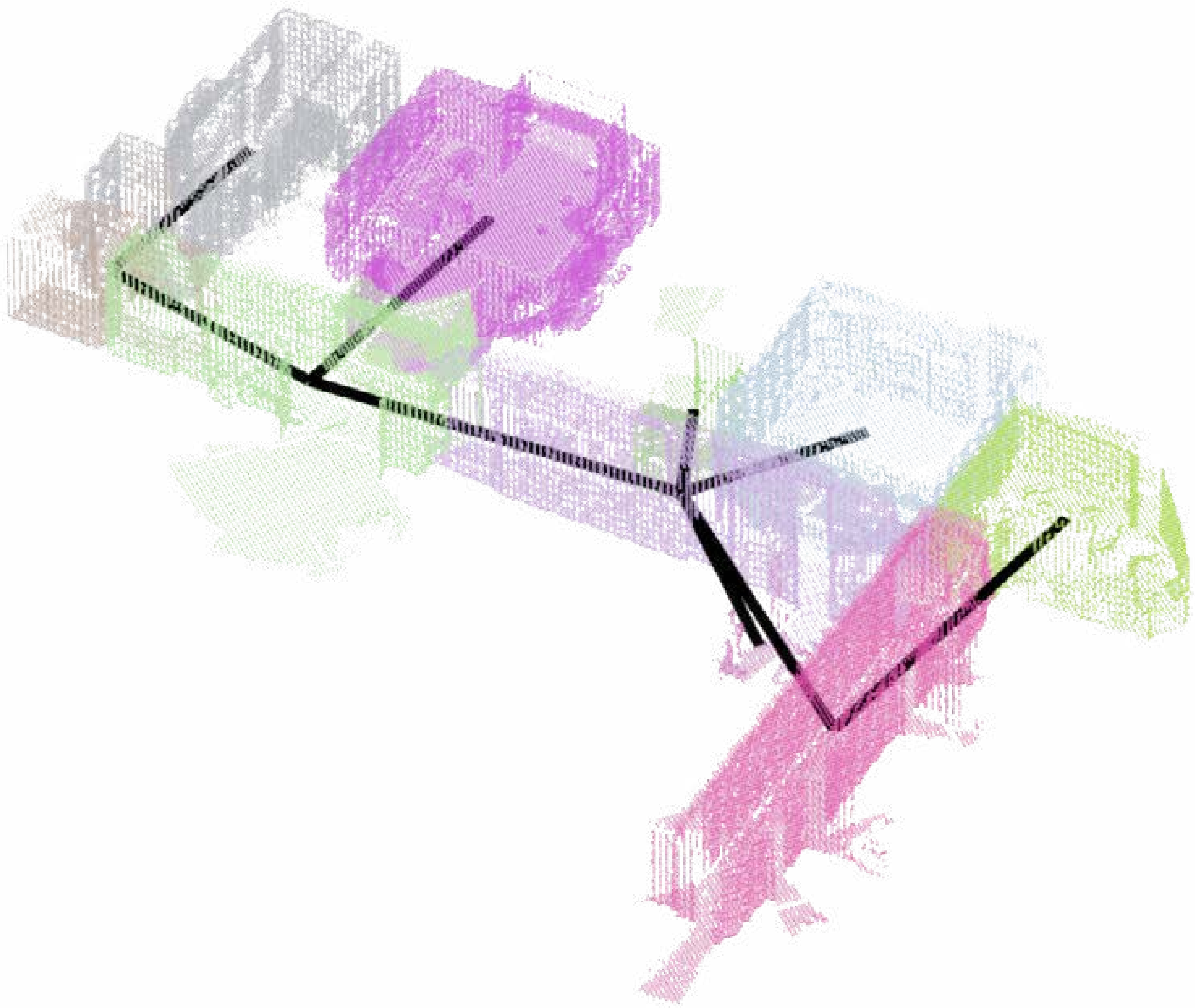

Figure 5: *Another example of a topometric map (van Schendel, 2022)*

# **Methodology** | Map extraction (overview)

- **Goal** extract partial topometric map from partial voxel grid map
- Navigation graph extraction
- Optimal view estimation
- Room segmentation / visibility clustering
- Topometric map extraction

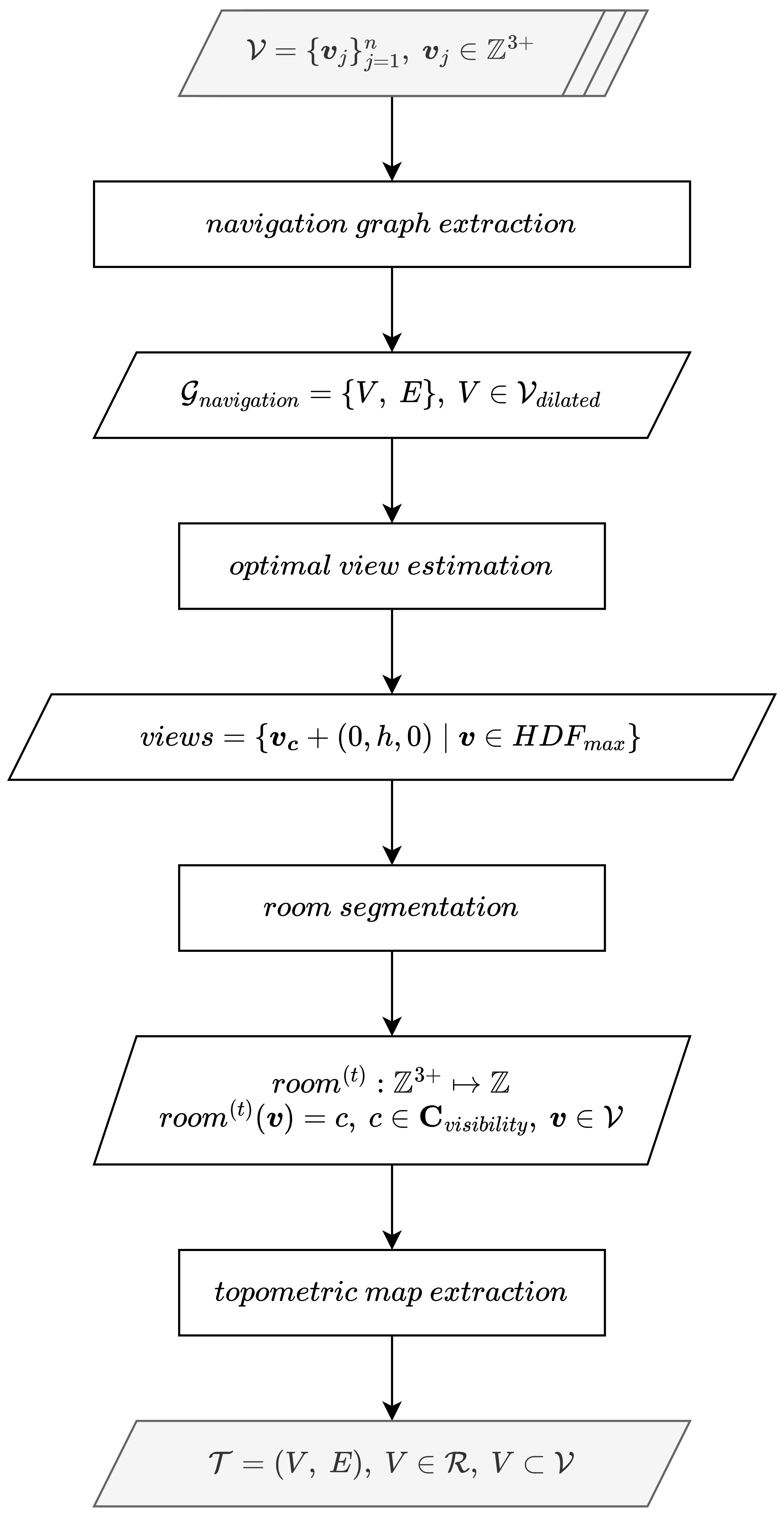


Figure 9: *Overview of map extraction methodology (van Schendel, 2022)*

# **Methodology** | Map extraction (navigation graph + optimal view estimation)



- Convolution with stick kernel
- Upward dilation
- Largest connected component
- Local maxima of horizontal distance field

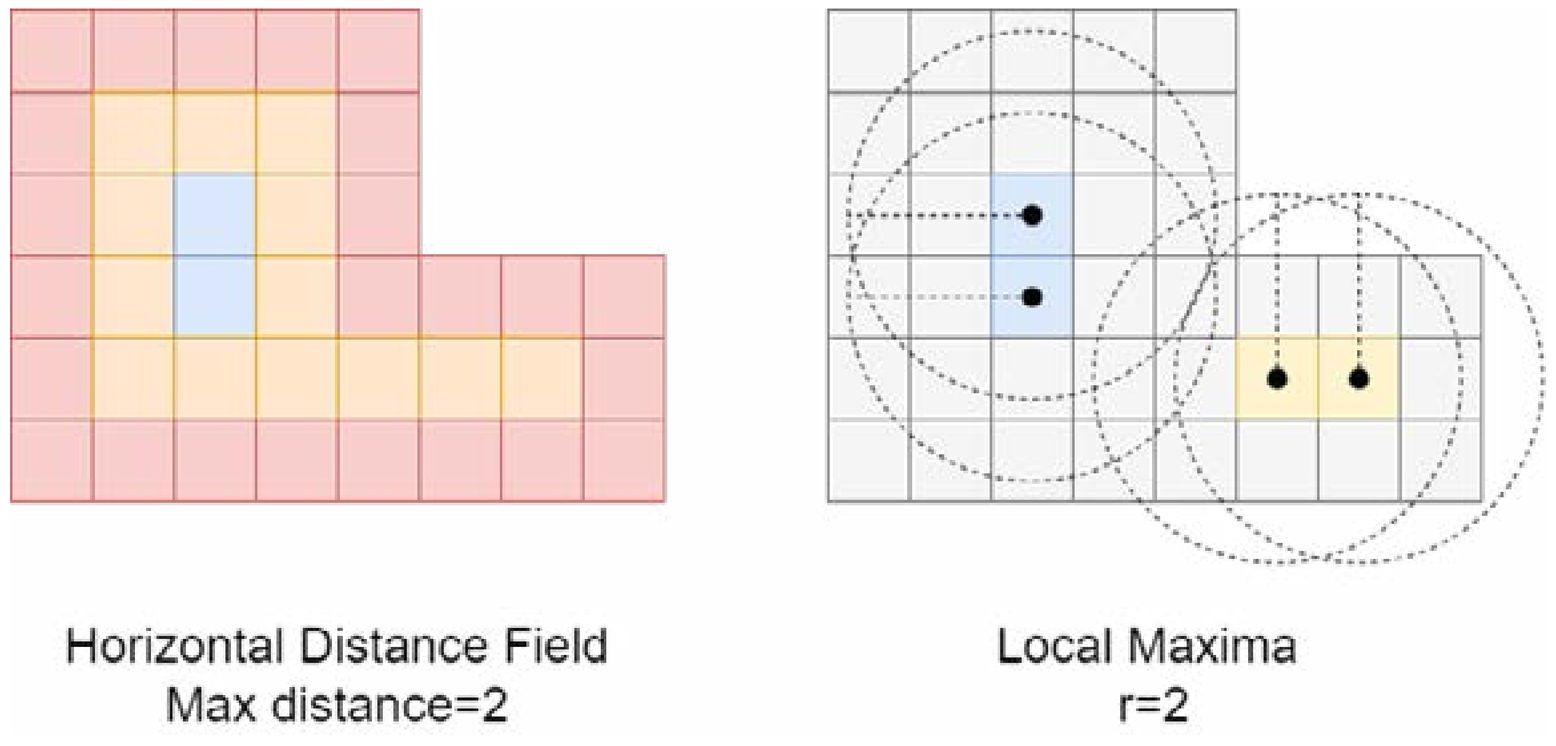


Figure 10: *Illustration of horizontal distance field maxima (van Schendel, 2022)*

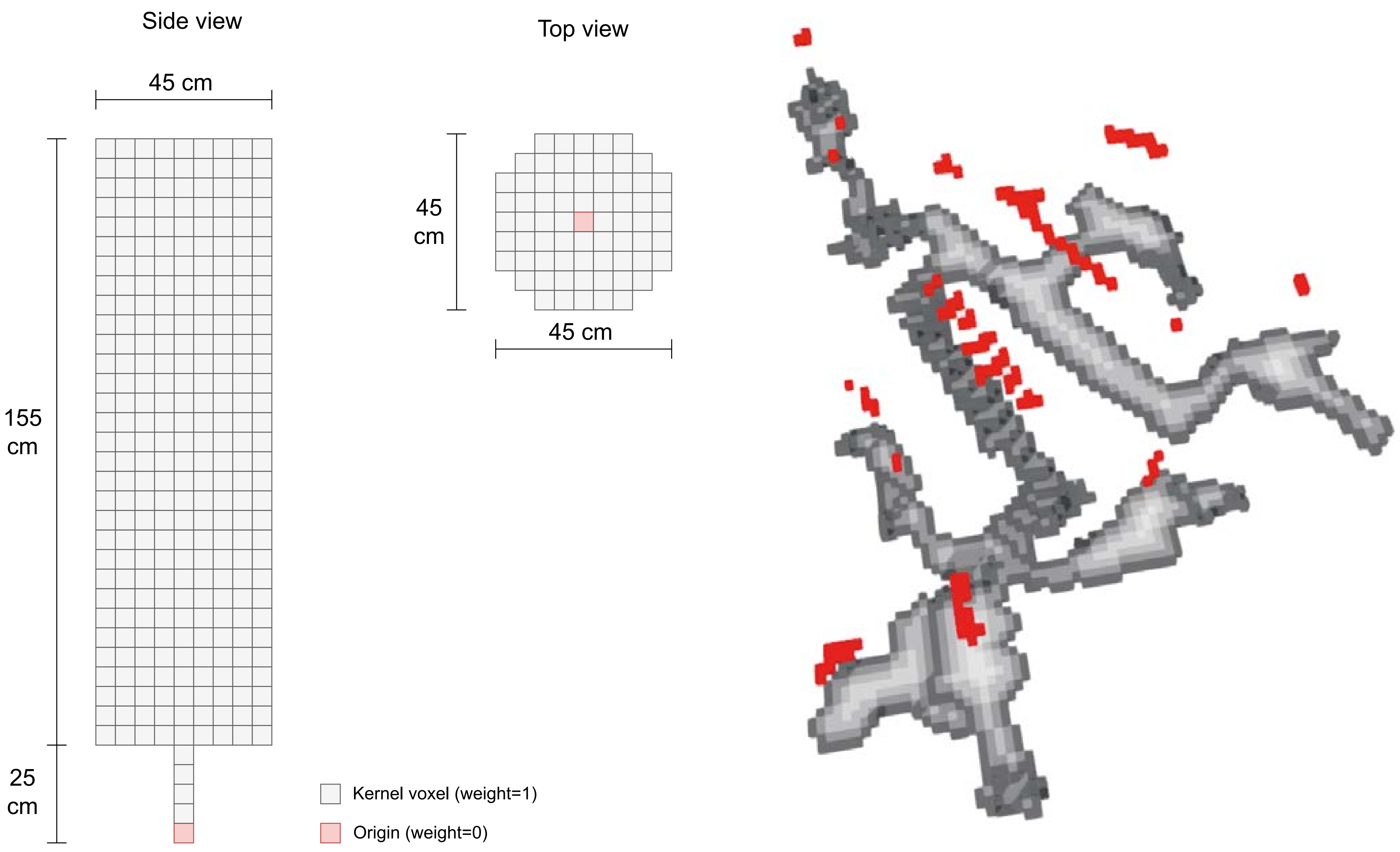


Figure 11: *(left) Stick kernel used to detect unobstructed voxels (right) example of navigation graph spanning two stories and resultant optimal views (van Schendel, 2022)*

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- Visibility computation
- Visibility clustering
- Label propagation

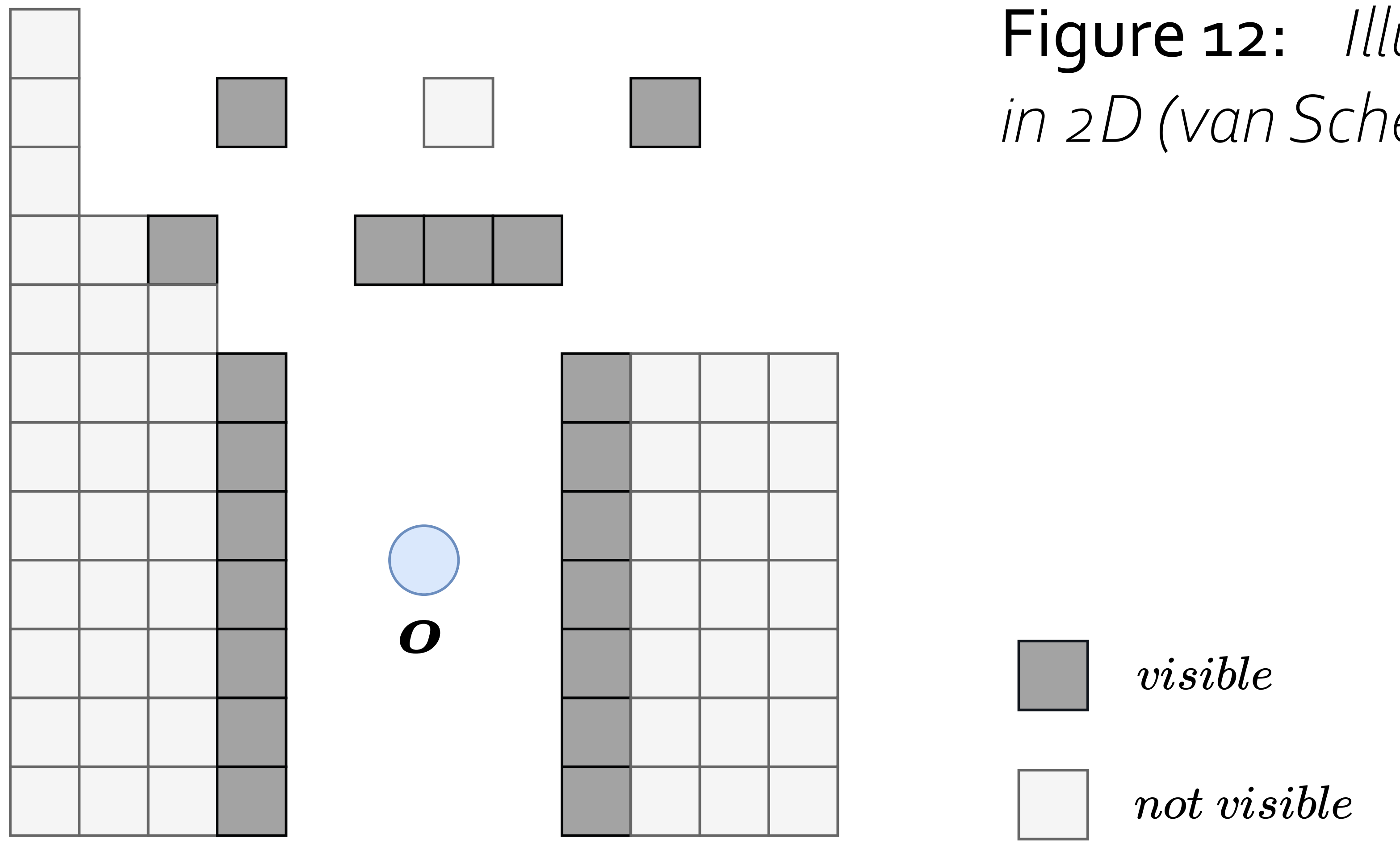


Figure 12: *Illustration of visibility in 2D (van Schendel, 2022)*

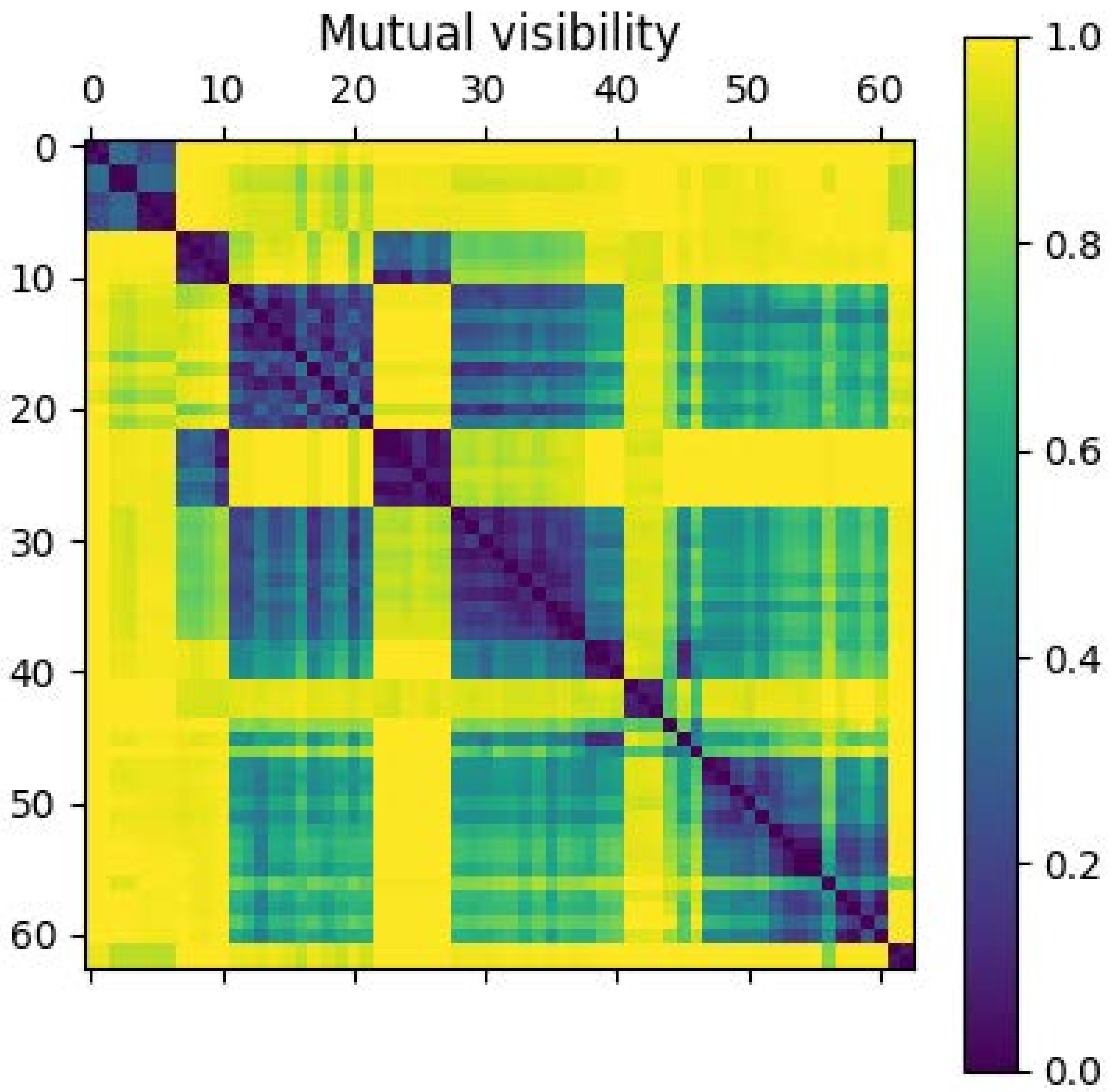


Figure 13: *Example of a mutual visibility matrix (van Schendel, 2022)*

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- **Goal** find the nodes in two partial topometric maps that represent the same rooms
- Geometric descriptor
- Contextual embedding
- Hypothesis growing

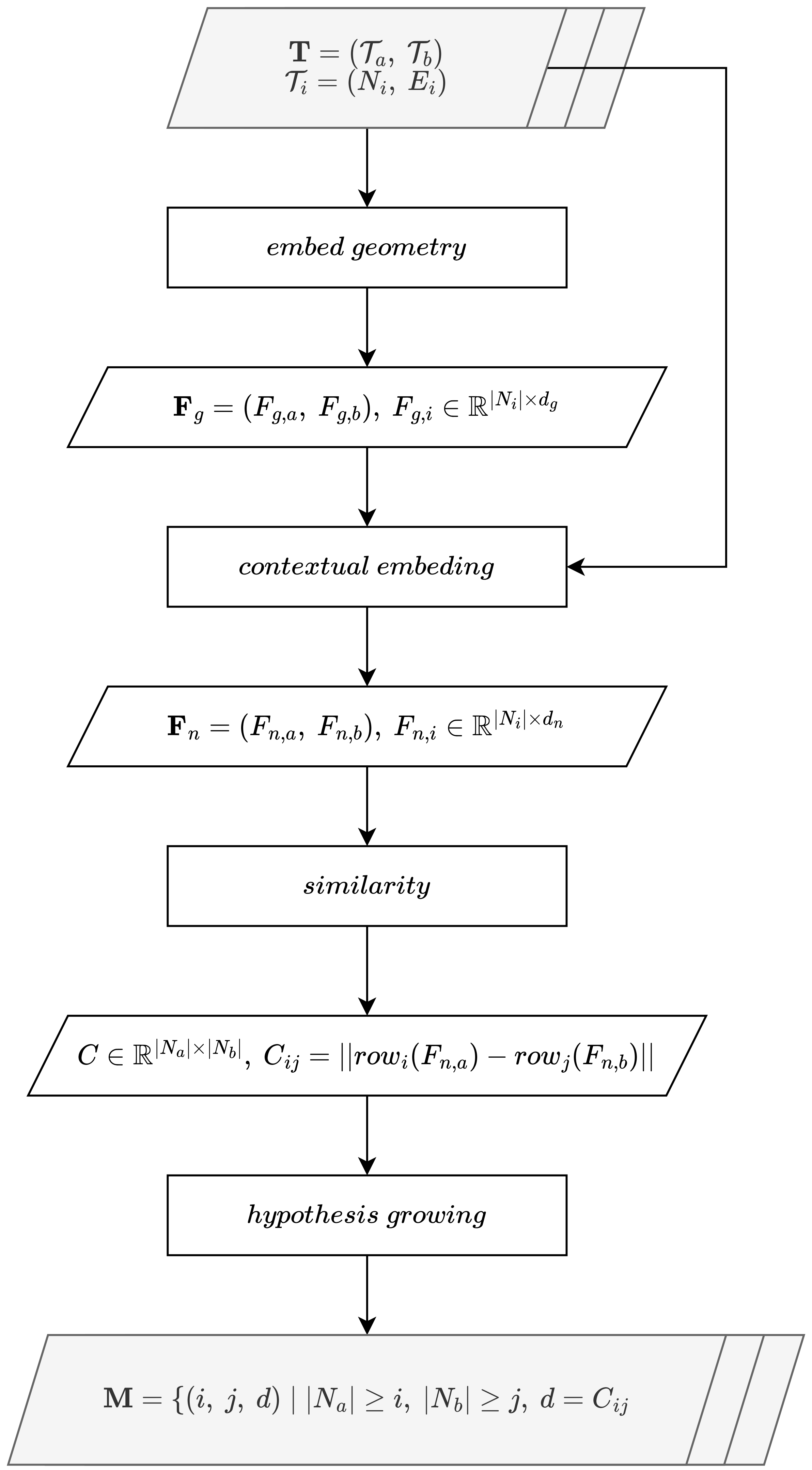


Figure 14: *Overview of map matching methodology (van Schendel, 2022)*

- Geometric descriptor using spectral and deep learning approaches

- Combine descriptor with descriptor of nodes within multiple steps in topological graph

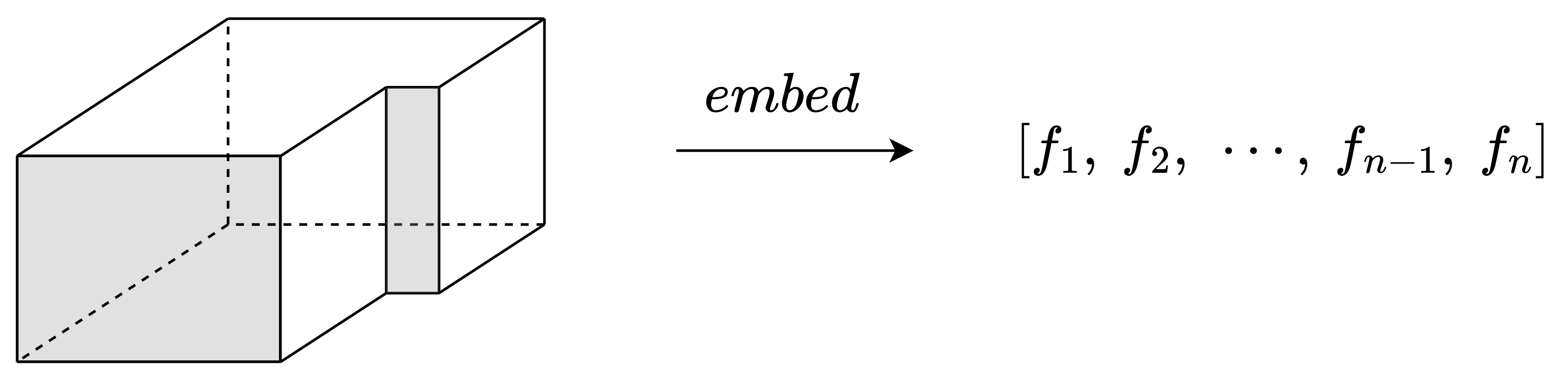


Figure 15: *Illustration of geometric descriptor (van Schendel, 2022)*

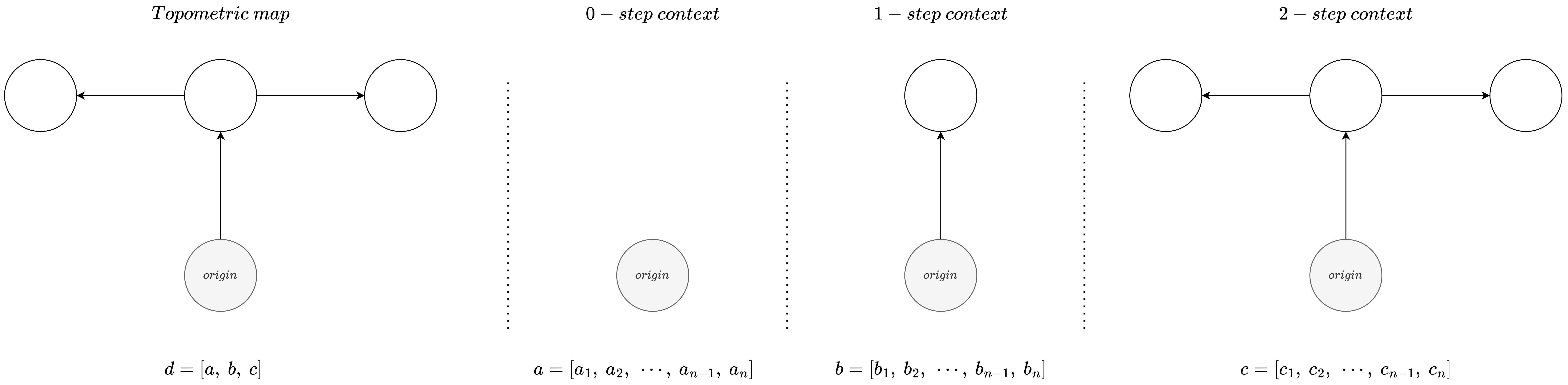


Figure 16: *Diagram showing 2-step contextual embedding (van Schendel, 2022)*

# **Methodology** | Map matching (hypothesis growing)



- Grow outwards from initial matching

- Constain growing based on similarity and align-ment

- Select best hypothesis

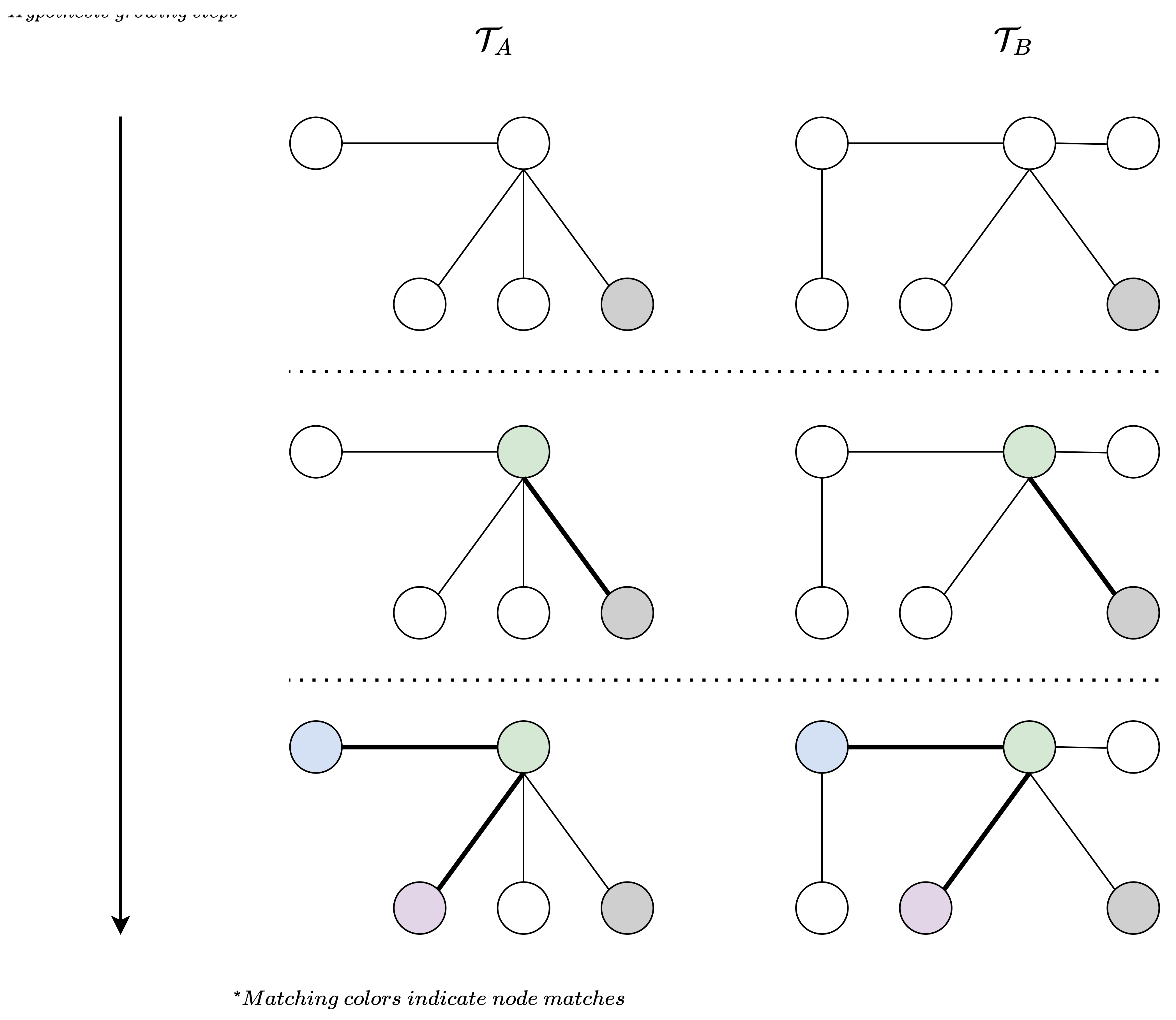


Figure 17: *Diagram showing hypothesis growing (van Schendel, 2022)*

- Goal combine partial topometric maps into one global topometric map using identified matches
- Gravity-aligned registration of matches
- Transformation clustering
- Hypothesis selection
- Topometric map extraction

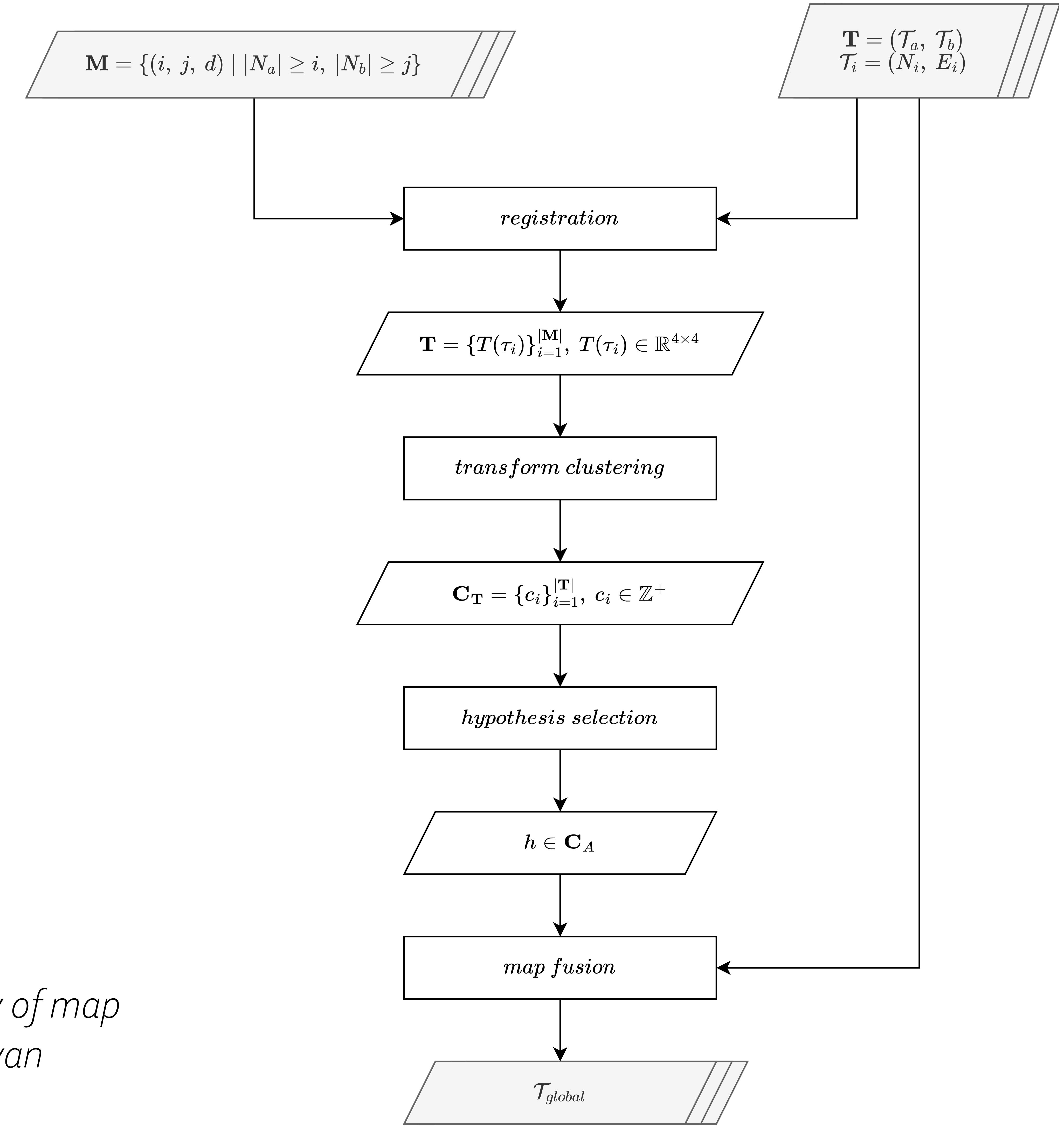


Figure 18: *Overview of map fusion methodology (van Schendel, 2022)*

- Stanford 3D Indoor Dataset (S3DIS) / CSLAM Dataset (Chen et al, 2020; Golodetz et al, 2018)

- Simulated partial maps
  - Visibility computation
  - Manually created trajectories

- Manually annotated topological graph and room segmentation.

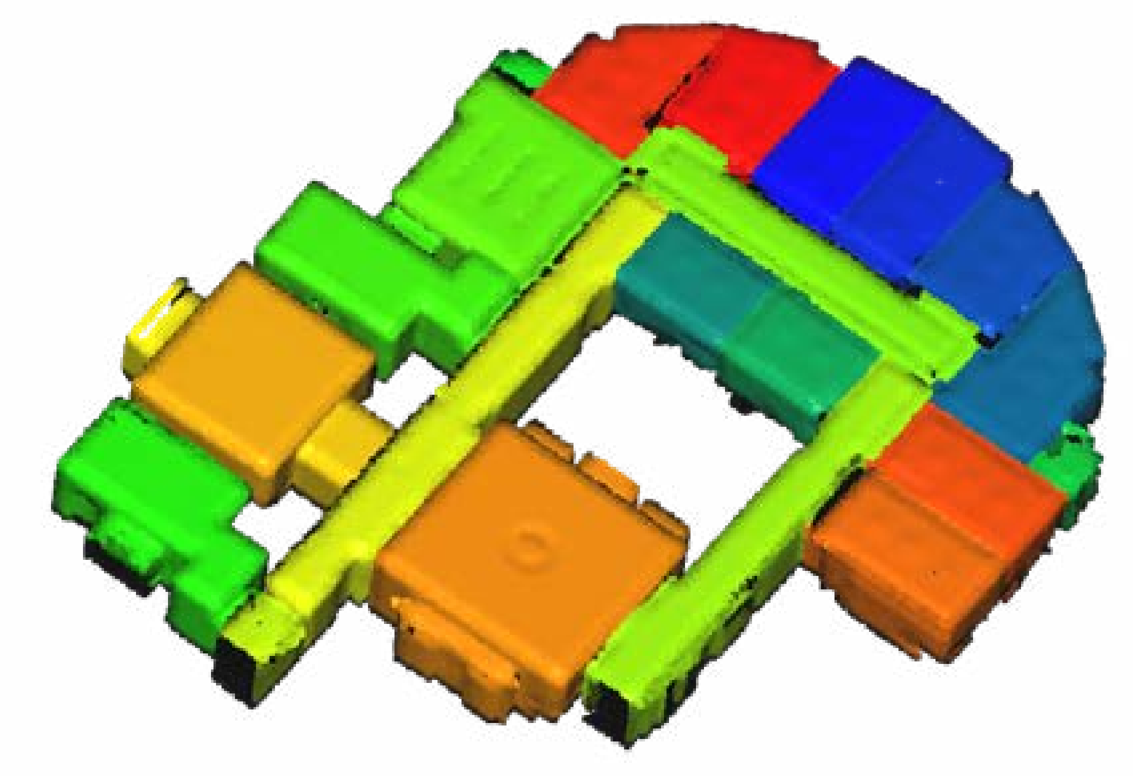

Figure 19: *Area 3 of S3DIS with ground truth room segmentation (van Schendel, 2022)*

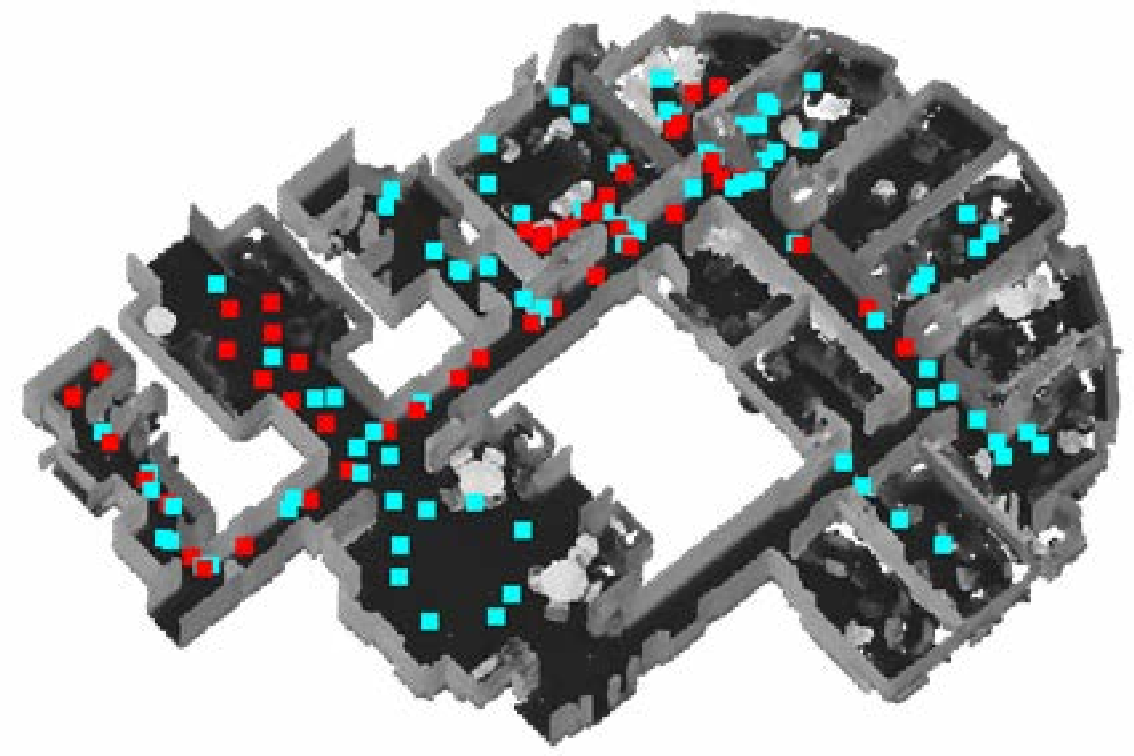

Figure 20: *Two simulated scanning trajectories in red and blue (van Schendel, 2022)*

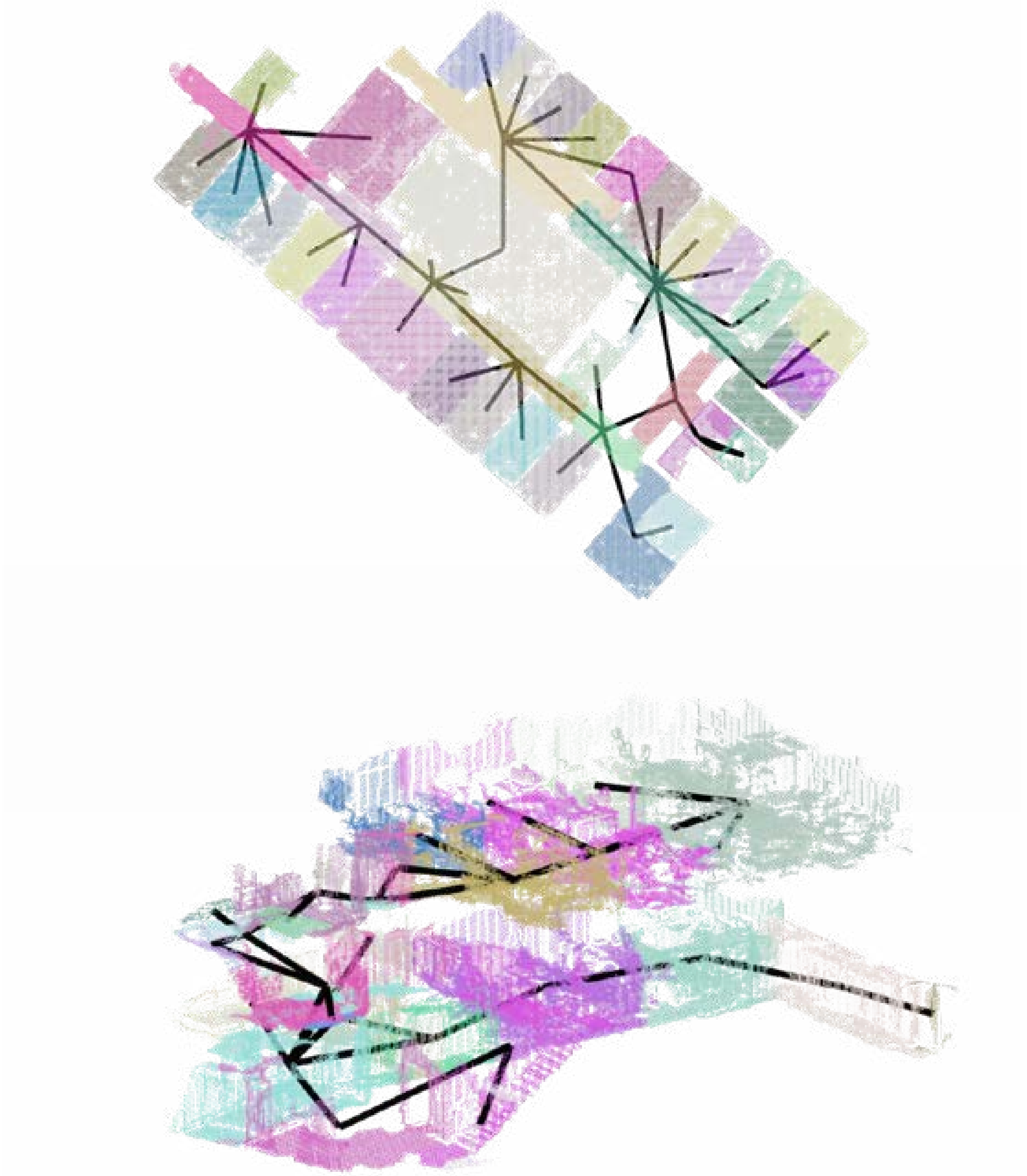

Figure 21: *Results of our map extraction approach for 1 and 2 storey environments (van Schendel, 2022)*

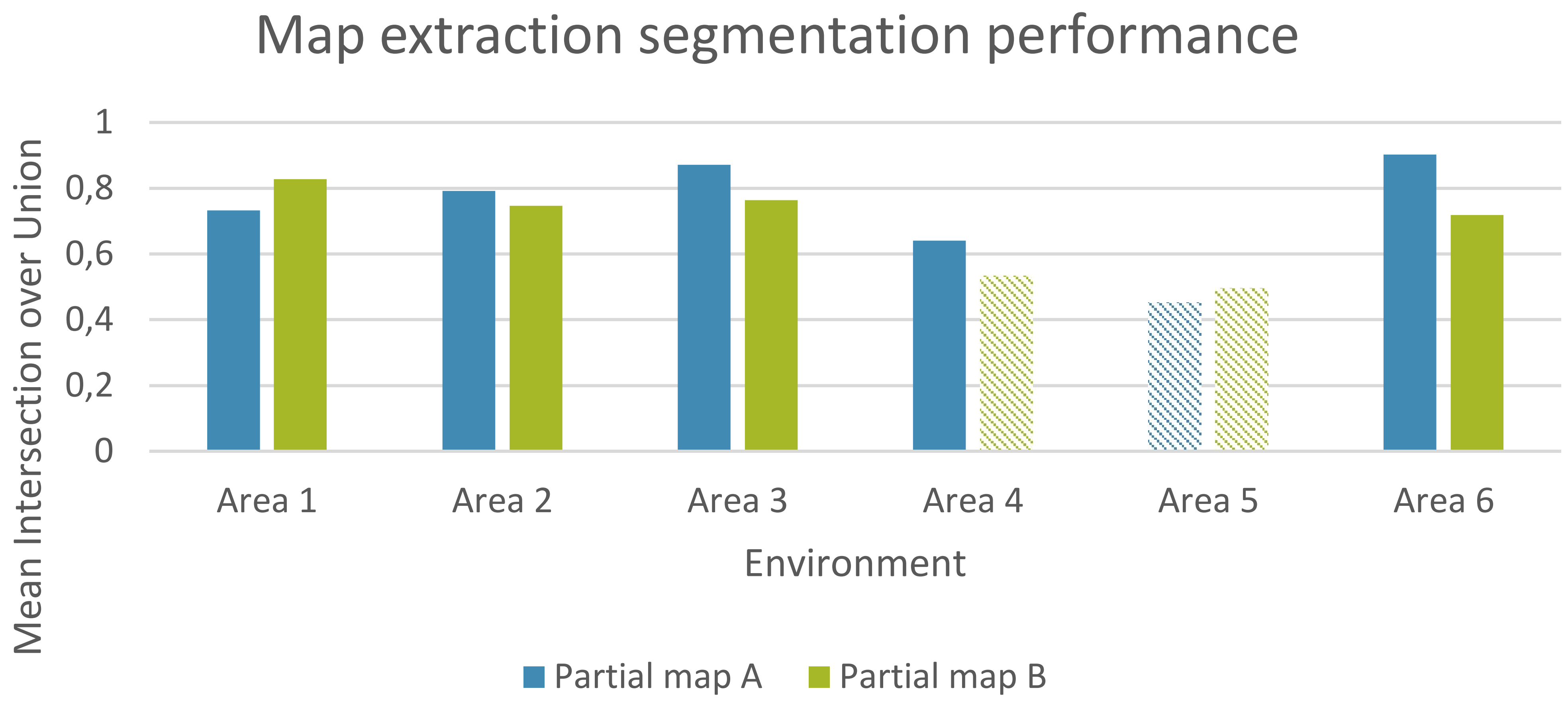


Figure 22: *Mean Intersection over Union for each partial map in S3DIS dataset (van Schendel, 2022)*

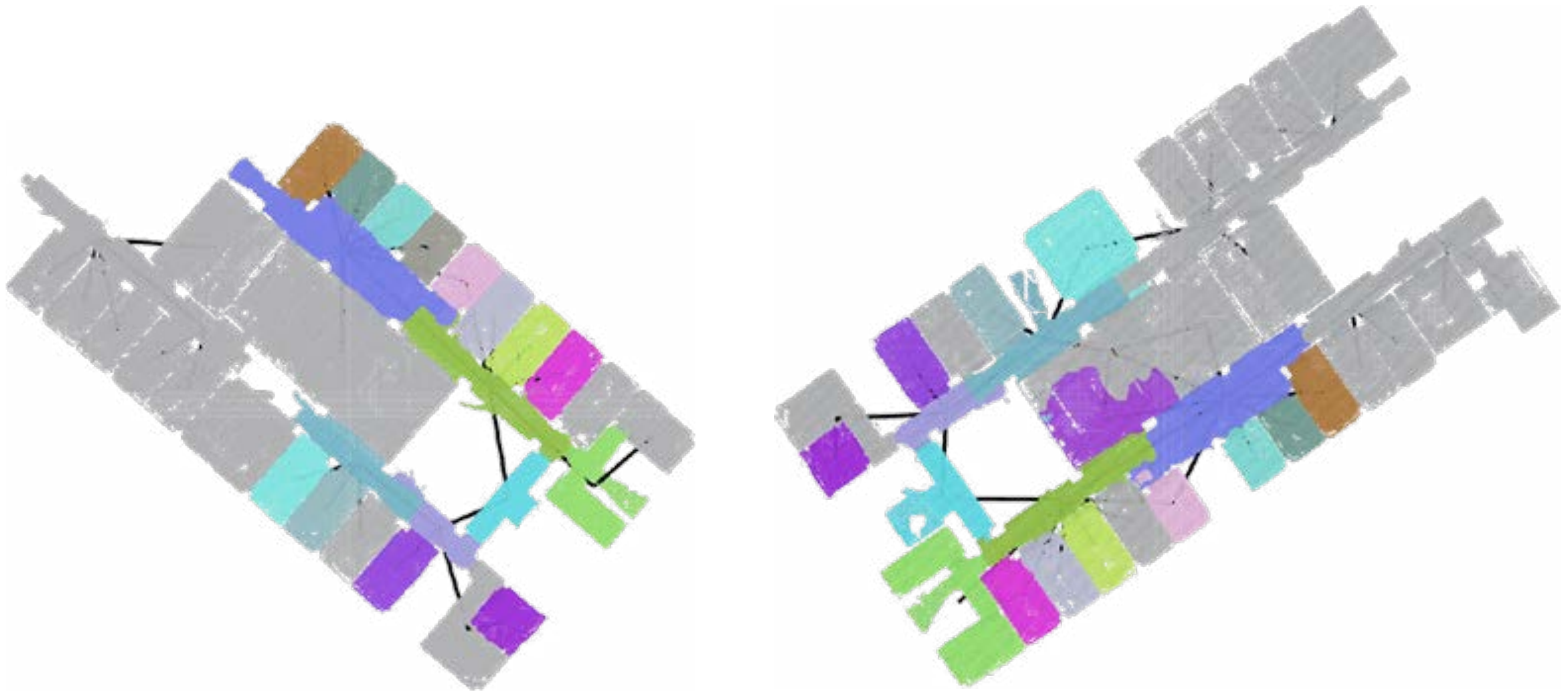

Figure 23: *Map matching results for area 1 of S3DIS dataset using spectral descriptors, 1-step contextual embedding and hypothesis growing (van Schendel, 2022)*

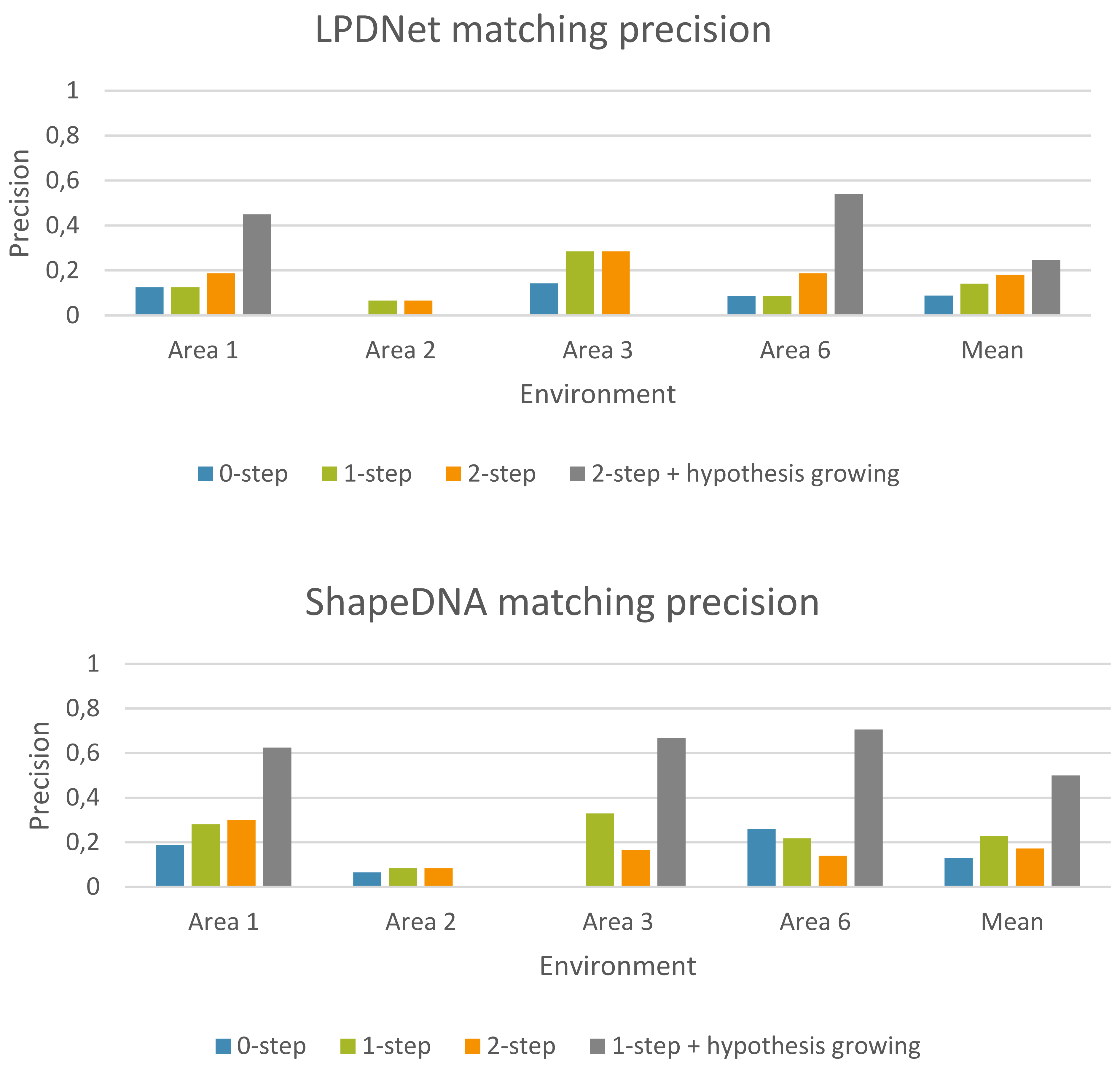


Figure 24: *Map matching accuracy for both descriptor approaches (van Schendel, 2022)*

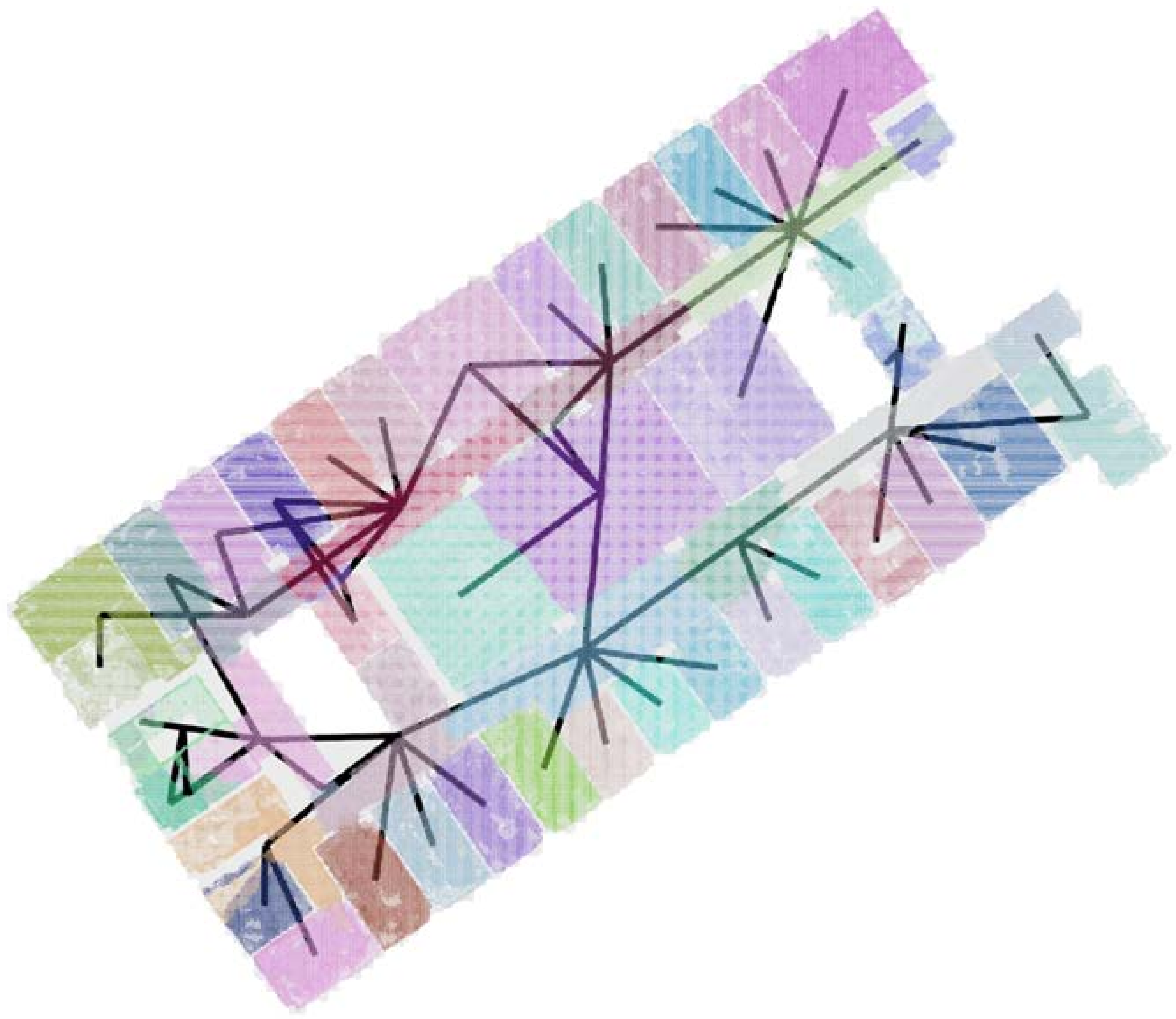

Figure 25: *Map fusion results for area 1 of S3DIS dataset using matches from previous section (van Schendel, 2022)*

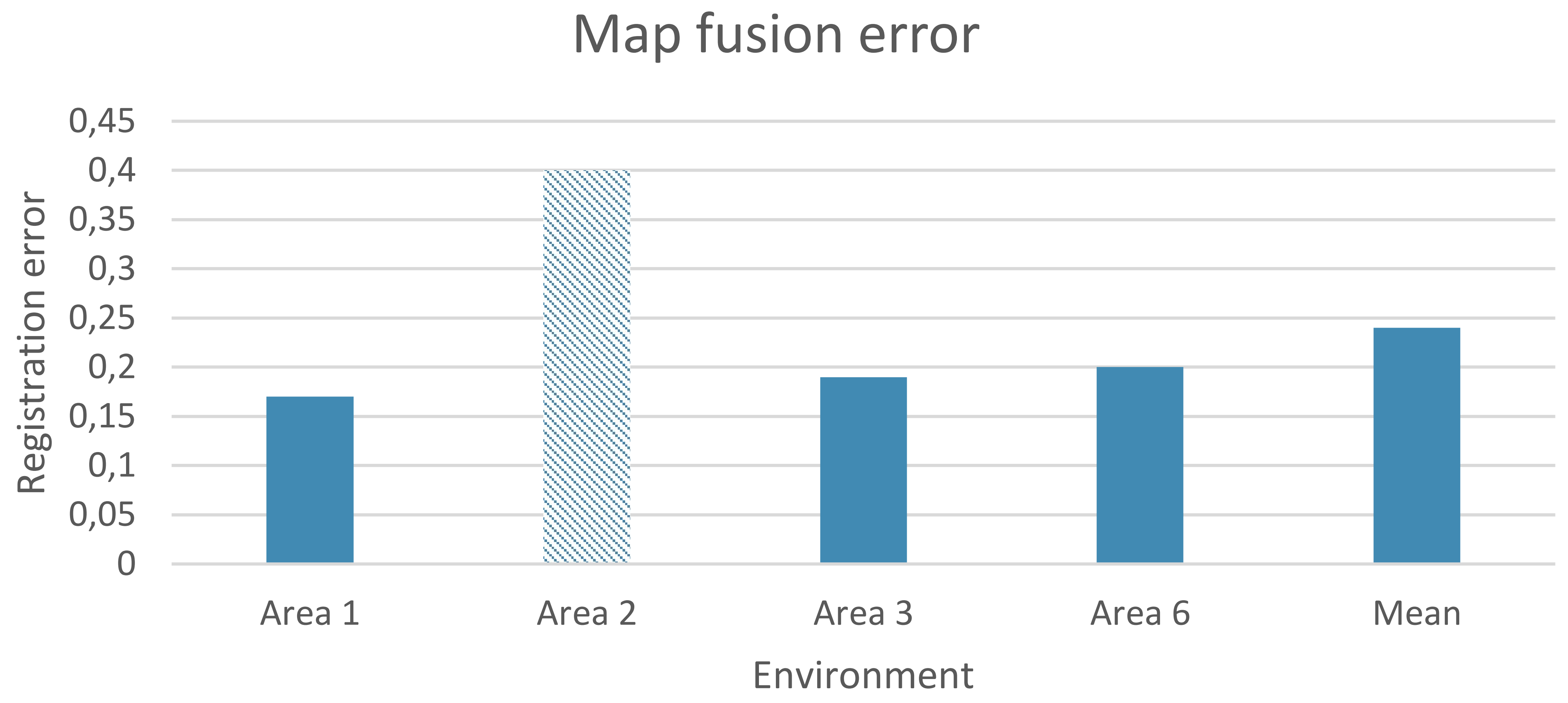


Figure 26: *Map fusion results for each area in S3DIS dataset for which map extraction did not fail (van Schendel, 2022).*

- Map extraction
  - close to ground truth
  - often oversegmented
  - navigation graph not robust enough.
  - absence of ceilings worsens performance

- Map matching
  - baseline descriptor performance is bad
  - contextual embedding and hypothesis growing improve it significantly

- Map fusion
  - performs well, even with small amount of matches
  - Wrong results detectable, can filter out wrong matches
  - direct fusion of topological graphs challenging

- Map extraction:
  - Navigation graph extraction with stick kernel works but not robust enough yet.
  - Room segmentation using visibility clustering

- Map matching:
  - Spectral embedding
  - Contextual embedding / hypothesis growing

- Map fusion:
  - Gravity-aligned registration
  - Transformation clustering / hypothesis selection

- **Conclusion** using topometric maps from map merging is feasible but more work remains.

# **Discussion & Conclusion** | Future work

- Robust navigation graph extraction
- Robust room segmentation
- Improved geometric descriptors
- One-to-many matching
- Non-rigid map fusion
- Multiway map merging

# References



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