Movement patterns with Voronoi Diagrams

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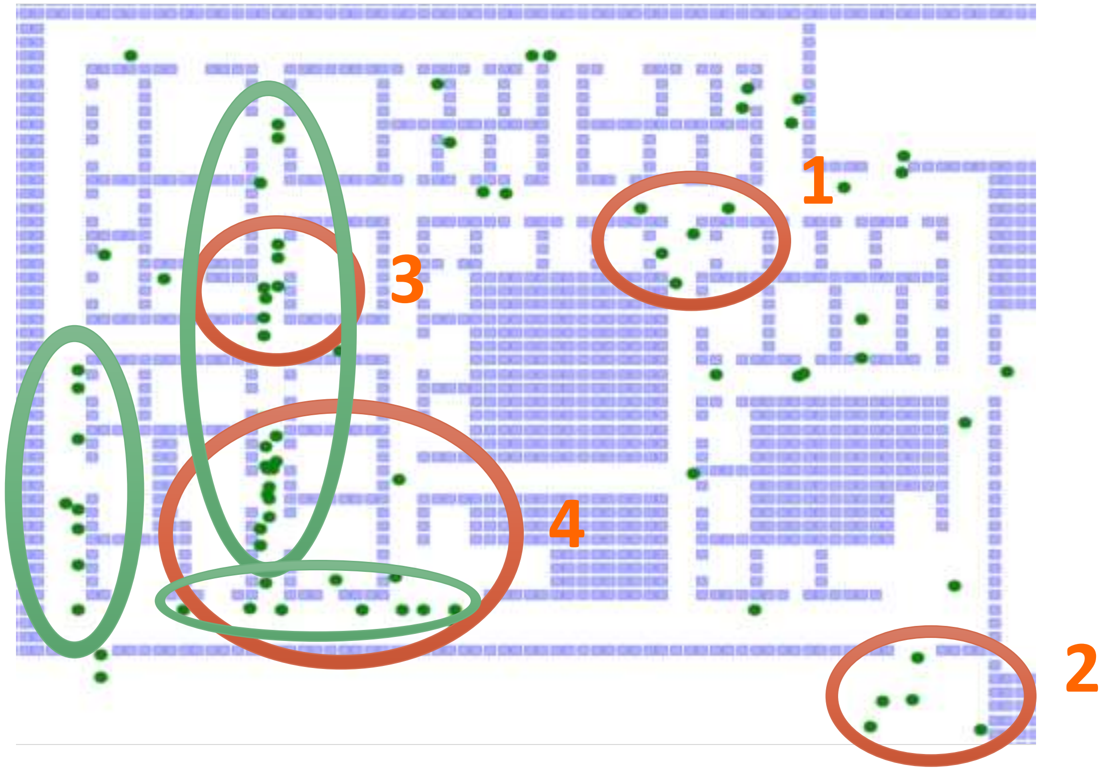
Motivation

- In clustering or point pattern analysis, relationships between neighbouring points may provide insights
- For example, queuing during evacuations

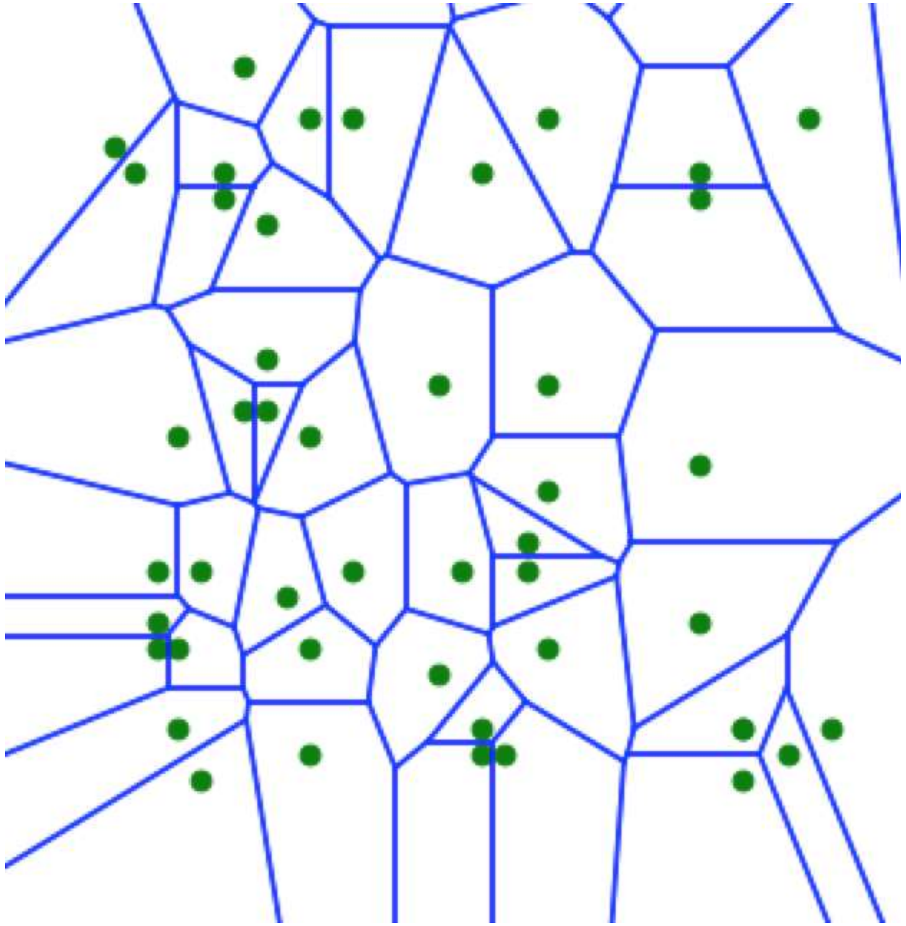


Method

- Voronoi cell properties

Voronoi diagrams

- Spatial data structure for nearest neighbour queries
- Voronoi cell or region
- Cell properties
  - Elongation
  - Orientation
  - Distance to neighbours
- Texture analysis



Proposed Voronoi Diagrams method

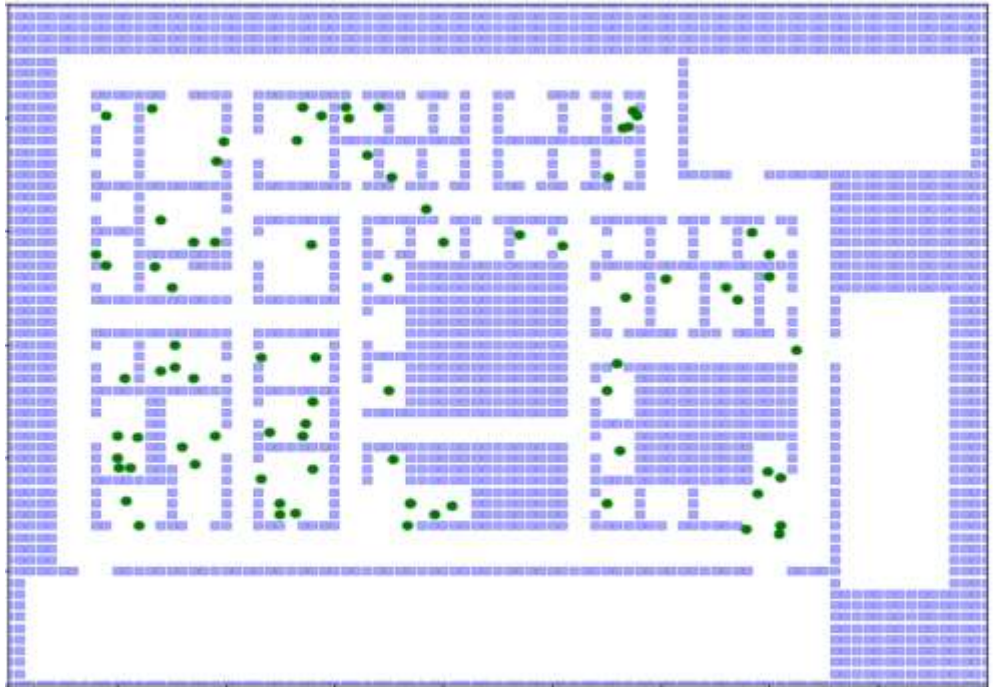
- Establish rules using voronoi cell properties (e.g. elongation, orientation) to **define** a pattern
- Within spatiotemporal data, if a point or group of points satisfies the rules, the pattern is said to be **identified**

Showcase

- Dataset
- Corridor cluster
- Transition pattern
- Experiment

Dataset

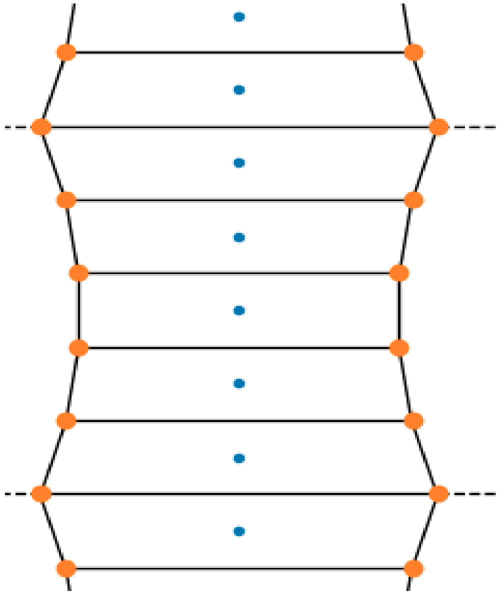
- Visual Analytics Science and Technology (VAST) challenge 2008
- Synthetic evacuation dataset
- Positional data from 80 people at each time step
- 800 time steps



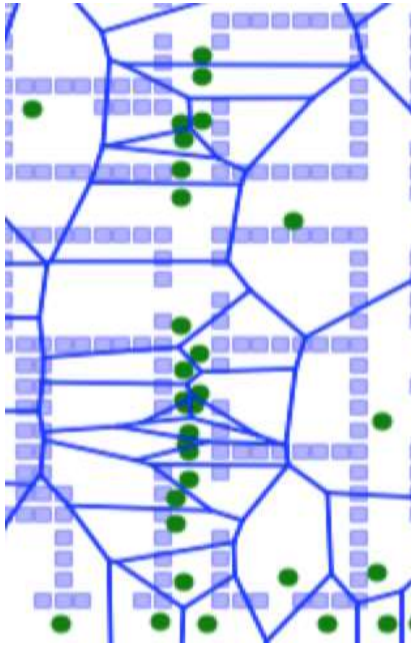
Corridor cluster

- Queue of points
- Define pattern using elongation, orientation and distance to neighbours

Perfect queue



Actual queue

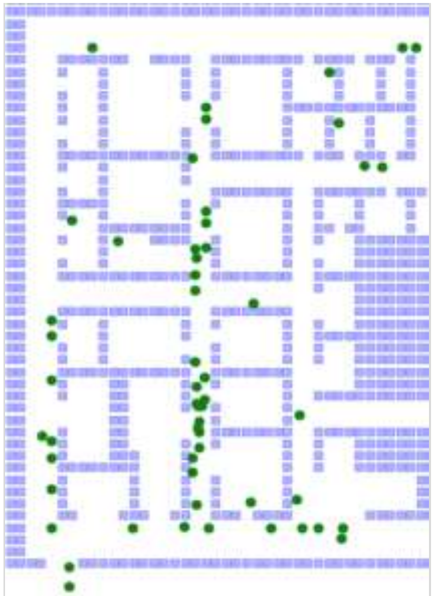


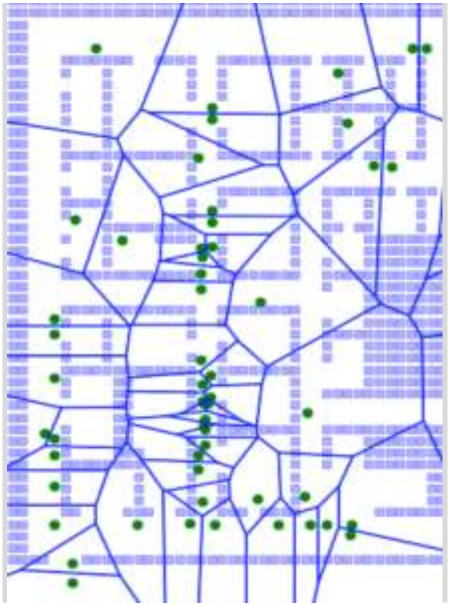
Corridor cluster

- Each neighbouring cells have a similarity score:

$$score(V_p, V_q) = \frac{W_E \cdot E(V_p) + W_O \cdot \Delta O(V_p, V_q) + W_D \cdot d(V_p, V_q)}{W_E + W_O + W_D}$$

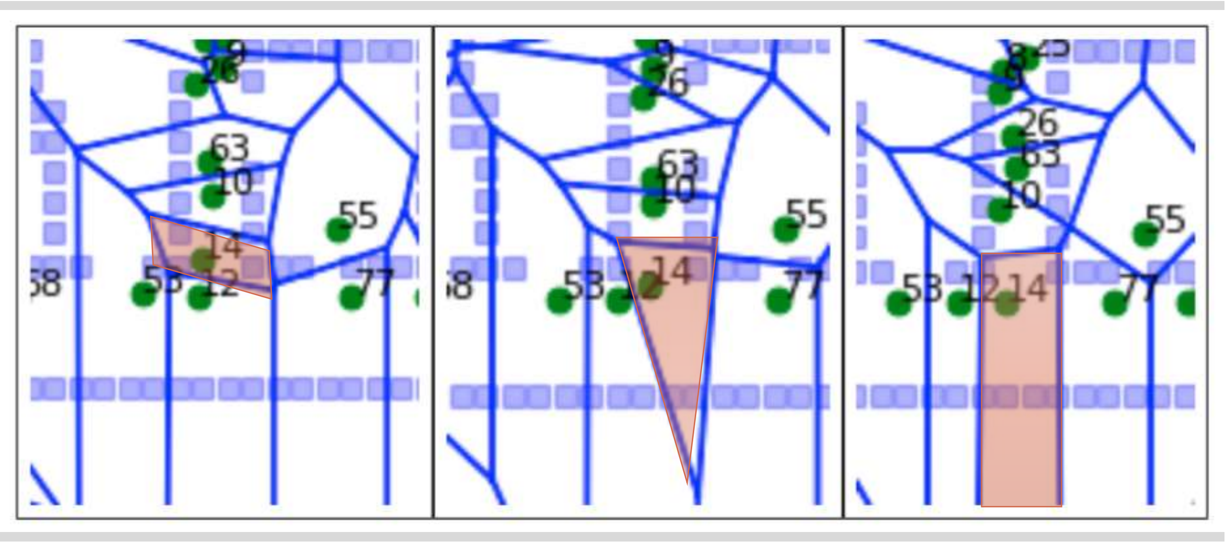
- Score uses elongation, orientation and distance as a weighted average
- If the score is larger than a threshold, then the two cells belong to the same cluster
- Score represents a tradeoff





Transition pattern

- Movement from one corridor to another
- We define 3 states for the cell
    - State 1 – Elongated, horizontal, more than three sides
    - State 2 – Three sides
    - State 3 – Elongated, vertical, more than three sides



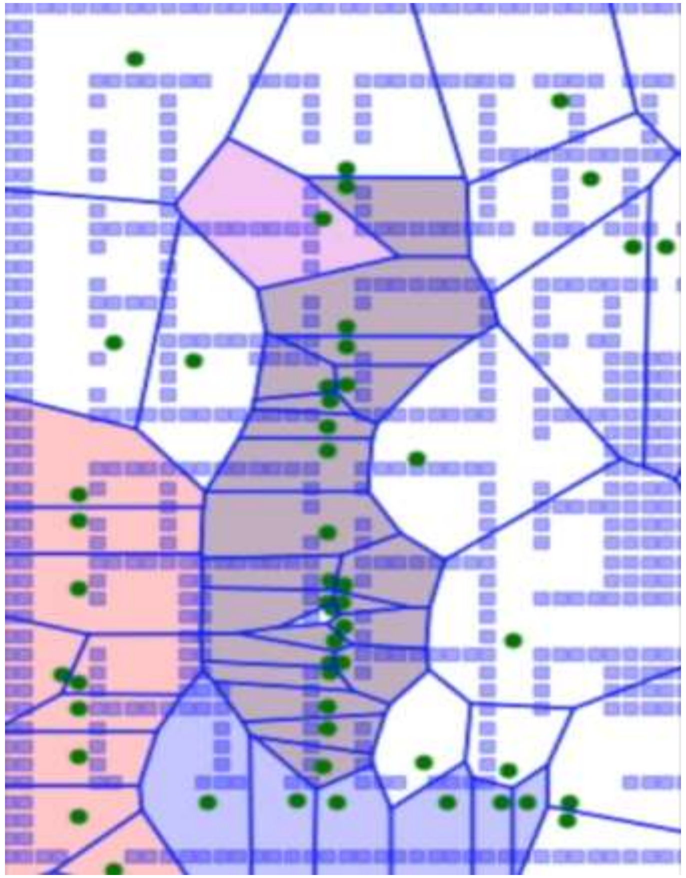
State 1 **State 2** **State 3**

Experiment

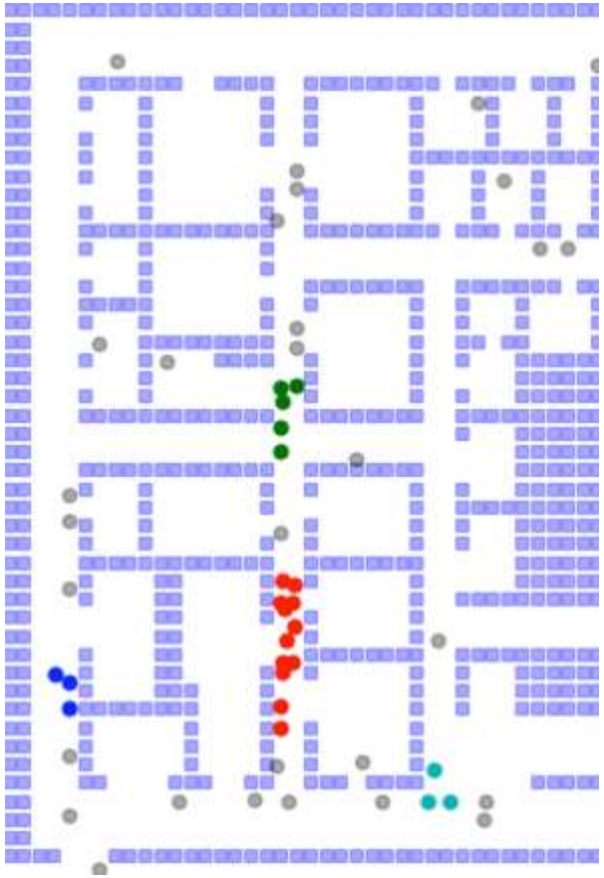
- Visual analysis
- Our method vs. baselines

Visual analysis – Corridor cluster

Voronoi cell properties



Distance



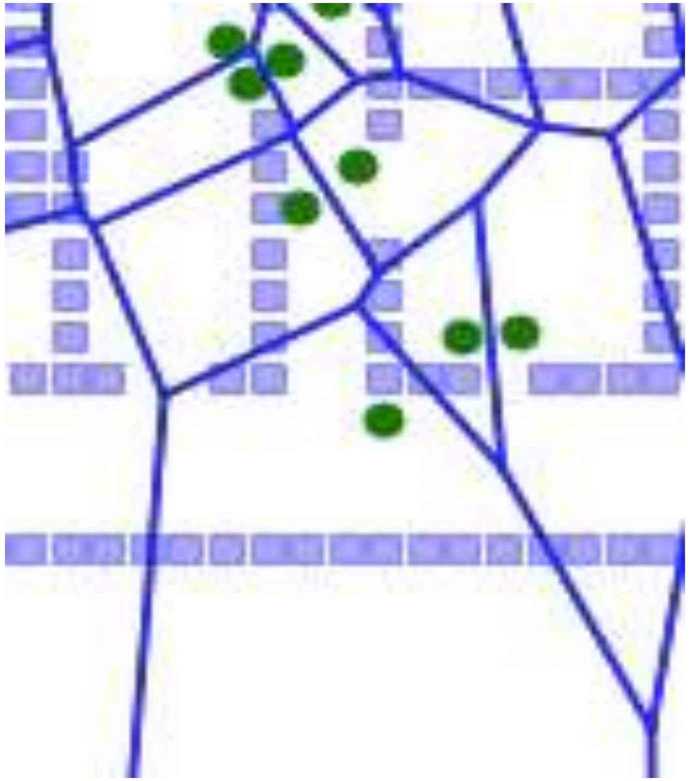
Results – Corridor cluster

- Experiments 1 and 2 are distance based clusters
- Experiments 3 – 5 are our method using different weights
  - Exp 3 – $W_E = {}^{1}/_{3}, W_O = {}^{1}/_{3}, W_D = {}^{1}/_{3}$
  - Exp 4 – $W_E = {}^{1}/_{6}, W_O = {}^{2}/_{6}, W_D = {}^{3}/_{6}$
  - Exp 5 – $W_E = {}^{1}/_{8}, W_O = {}^{1}/_{8}, W_D = {}^{6}/_{8}$

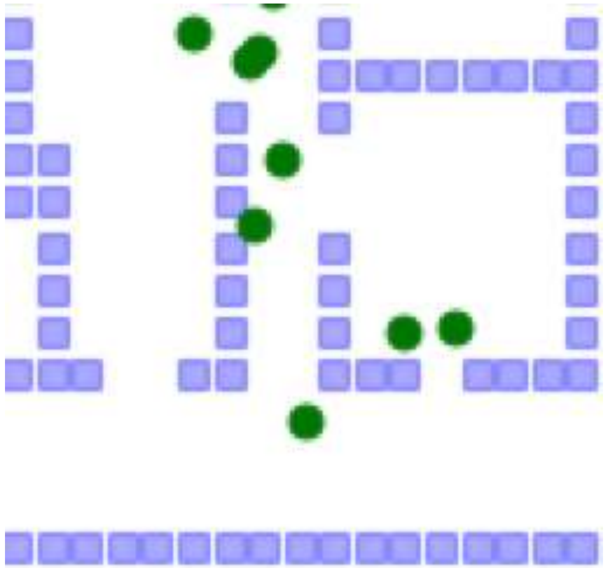
Exp.	Precision VC	Recall VC	F_1 VC	Precision HC	Recall HC	F_1 HC
1	0.85	0.76	0.80	0.72	0.52	0.60
2	0.60	**0.98**	0.74	0.74	0.18	0.23
3	**0.95**	0.14	0.24	**1**	0.15	0.25
4	**0.95**	0.62	0.75	0.99	0.67	0.80
5	0.91	0.92	**0.92**	0.87	**0.76**	**0.81**

Visual analysis – Transition pattern

Voronoi cell properties



Baseline



Results – Transition pattern

- Experiment 1 – 3 are naïve baselines using a simple trajectory rule
- Experiment 4 is our method using voronoi cell properties

Exp.	α	Precision	Recall	F_1
1	2	0.13	**1**	0.23
2	4	0.26	0.88	0.4
3	10	0.3	0.38	0.33
4	–	**0.6**	0.75	**0.67**

Conclusions

- Voronoi Diagrams may be used to perform fine-grained pattern analysis

- Corridor cluster better than distance-based clustering using weight combination
  - $W_E = {}^{1}/_{8}, W_O = {}^{1}/_{8}, W_D = {}^{6}/_{8}$
  - $F_1 = 0.92$ on VC
  - $F_1 = 0.81$ on HC

- Transition pattern better than naïve-rules pattern
  - $F_1 = 0.67$

Future work

- Use other properties such as eccentricity or size

- Check how rule flexibility affects pattern identification

- Perform a thorough time complexity analysis

Thank you