Spatial Visibility Clustering Analysis In Urban Environments Based on Pedestrians' Mobility Datasets

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Motivation

- 3D GIS.
- Spatial analysis in 3D urban environments.
- Research focused on visibility in open terrains.
- Urban environments – dense, complex, heterogeneous.
- 3D Visible volumes – fast and accurate.
- Clustering method based on visibility analysis.
- Generate optimal control points:
  - Pedestrian’s behavior analysis.
  - Emergency & Security - art gallery problem, HLS.
  - Entertainment events in urban scene.

Urban vs. Open Environments

- Open environments can be easily modeled with DEM / DTM.

- Urban environments:
  - Density – computational efficiency.
  - Data with high resolution – complexity.
  - 3D urban model.
  - Different kinds of objects (buildings, roads, vegetation etc).
  - Frequently changed (infrastructures).
  - Uncertainly (moving cars / peoples, lighting, weather).

Visibility Analysis - Previous work

- Viewshed *[Wang et al.96]*
  - Sightline computation and surfaces relationship
    - Limited for DEM models – Open terrains
    - Slow and inefficient
- Openness *[Fisher-Gewirtzman et al. 03]*
  - Urban design environment - DEM
  - Space Openness Index (SOI)

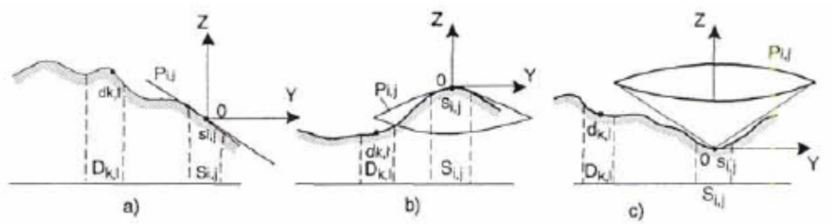
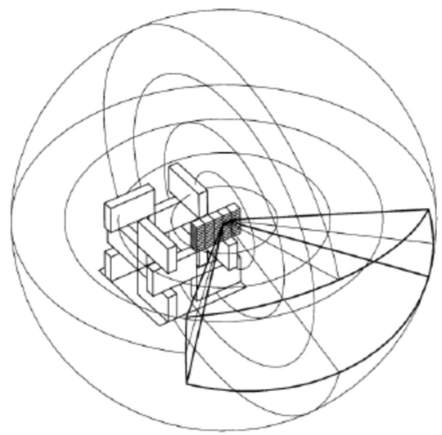


Figure 7. (a) If $d_{k,l}$ is not above $P_{i,j}$, it is invisible from the source point. (b) and (c) If $d_{k,l}$ is not above the circular conic surface $P_{i,j}$, it is invisible from the source cell.

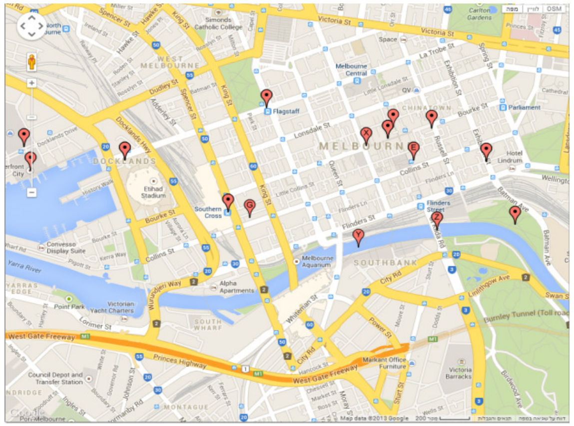
Wang et al. 96



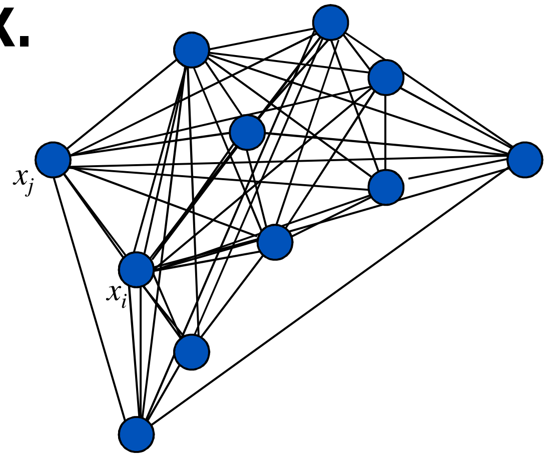
Fisher et al. 2003

Spatial Visibility Clustering (SVC) Method

- **Our data set $\{X_{i,j}\}$, i=1,2,..,n; j=1,2,..,p, consists of p features measured on n independent observation.**
- **We clustered the data into k clusters, $C_1, C_2 \ldots C_k$.**
- **The spatial meaning can be simplified as a group of viewpoints with minimal difference to the average visible volume in the same bounding box.**



Sensors Location for Monitoring Pedestrians' Mobility Data.



Pedestrians' location architecture based on monitoring datasets, observation points marked with blue circles.

Spatial Visibility Clustering (SVC)

- **For cluster *r* denote as C_r with n_r observations:**

$$V_r = \sum_{i \in C_r} \sum_{j \in C_r} \left\| V(x_i) - V(x_j) \right\|$$

$$V_r = \sum_{i \in C_r} \left\| V(x_i) - V(\bar{x}) \right\|$$

$$T_k = \sum_{r=1}^{k} \frac{1}{S} V_r$$

Where:

V(x) denotes the visible volumes from a viewpoint *x* bounded in volume *S*.

V_r is the sum of the absolute visibility differences of all viewpoints from visibility mean.

T_k - normalized visible volumes for all clusters *r=1..k*.

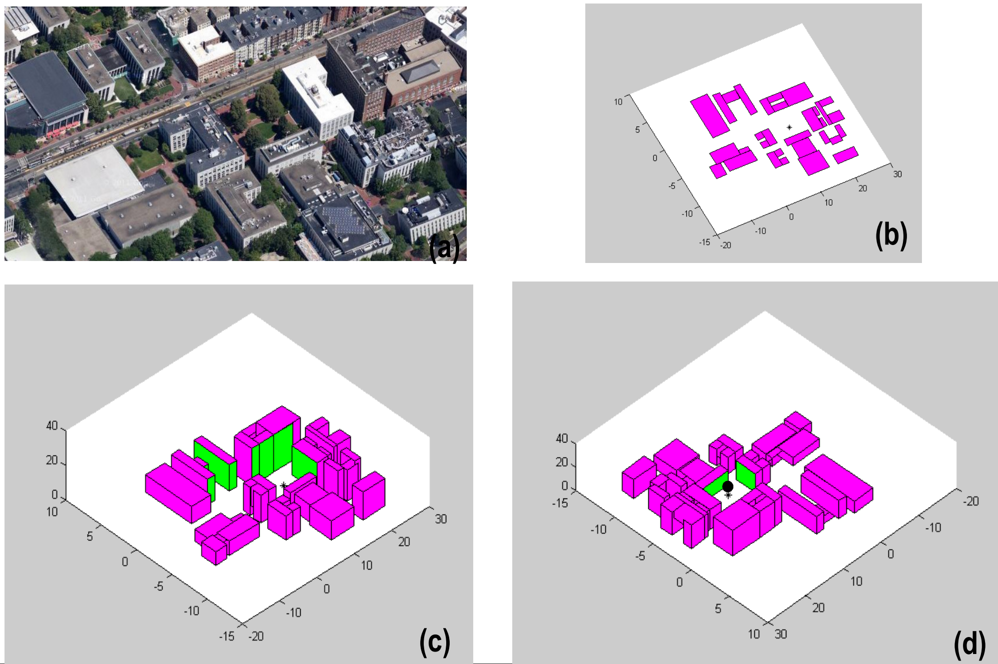
SVC – Main Steps

- Calculate the sum of absolute visibility differences of all points from their cluster visibility mean. Normalize this sum for all possible clusters T_k, also called *dispersion*.
- Generate a set of reference datasets, inside bounding volume *S*.
- Calculate the dispersion of each of these reference datasets.
- Define SVC for each possible number of clusters as: Expected dispersion of reference datasets - Dispersion of original dataset, $SVC_n(k) = T_k^* - T_k$.
- Set number of groups *k*, using well-known *F-test* function:

$$F_k = SVC_n / SVC_{n+1}$$

Analytic 3D Visibility Volumes Analysis

- Fast 3D visible volumes analysis in urban environments, based on an analytic solution.
- Plays major role in SVC method estimating the number of clusters.
- We extend our previous work for surfaces visibility analysis, and present an efficient solution for visible volumes analysis in 3D.



Gal & Doytsher 2012

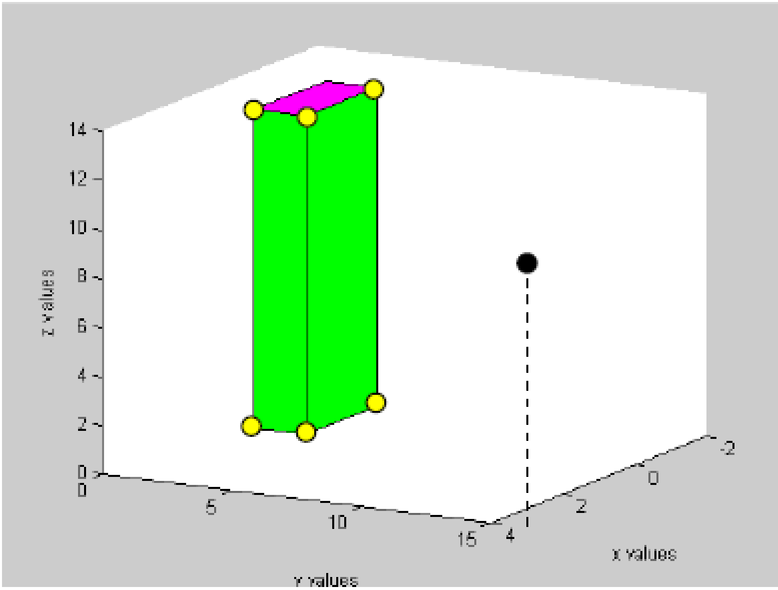
Visible Boundary Points (VBP)

- Based on our previous work, visibility boundary can be efficiently computed, defined as VBP.

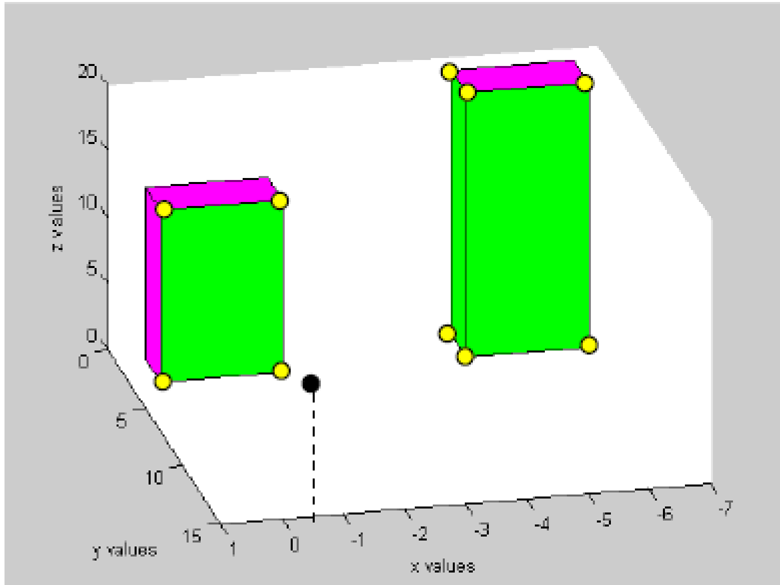
Visible Boundary Points (VBP) - we define VBP of the object i as a set of boundary points $j = 1..N_{bound}$ of the visible surfaces of the object, from viewpoint $V(x_0, y_0, z_0)$.

$$VBP_{i=1}^{j=1..N_{bound}}(x_0, y_0, z_0) = \begin{bmatrix} x_1, y_1, z_1 \\ x_2, y_2, z_2 \\ .. \\ x_{N_{bound}}, y_{N_{bound}}, z_{N_{bound}} \end{bmatrix}$$

Visibility Computation –Example



(a)

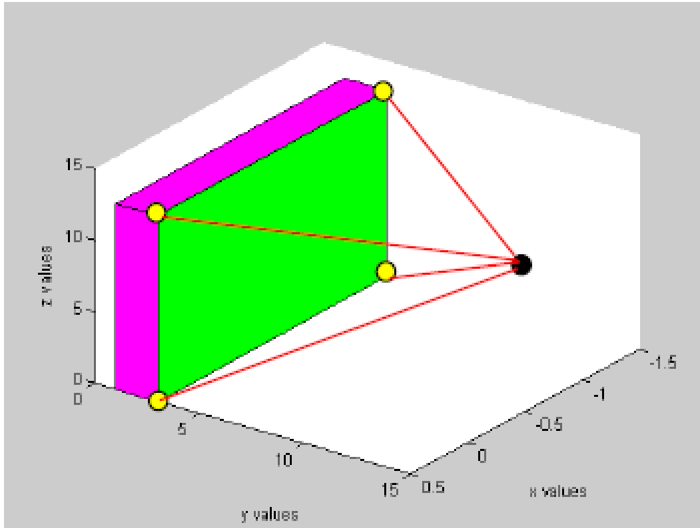


(b)

Visibility Volume computed with the Analytic Solution. Viewpoint is marked in black, visible parts colored in green, and invisible parts colored in purple.
VBP marked with yellow circles - (a) single building; (b) two non-overlapping buildings.

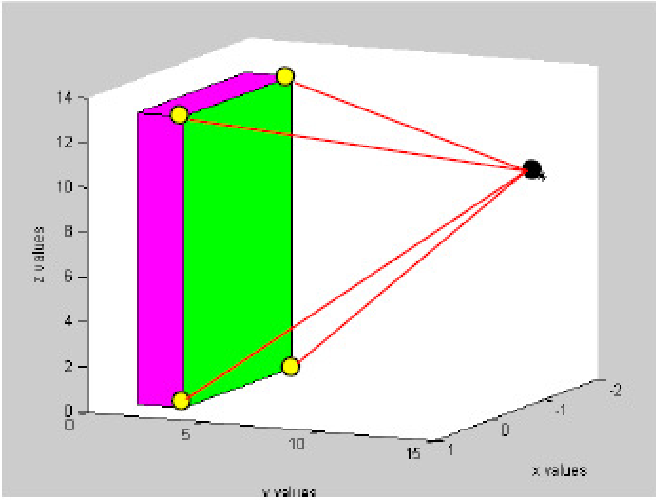
Visible Pyramids (VP)

Visible Pyramid (VP) – we define $VP_i^{j=1..N_{surf}}(x_0, y_0, z_0)$ of the object i as a 3D pyramid generated by connecting VBP of specific surface j to a viewpoint $V(x_0, y_0, z_0)$. Maximum number of for a single object is three.

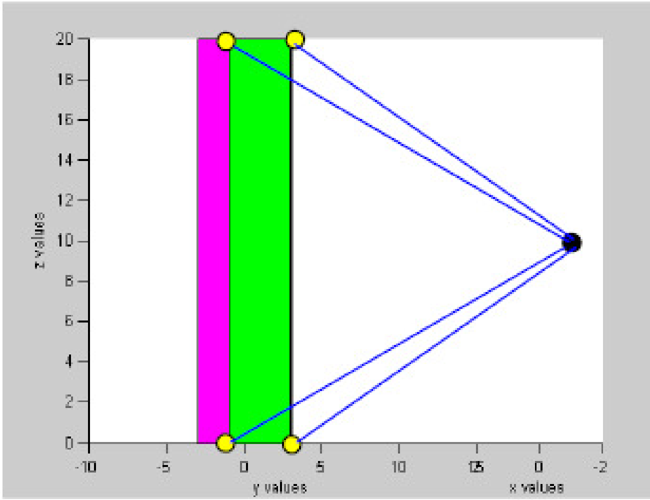


A Visible Pyramid from a viewpoint (marked as a black point) to VBP of a specific surface

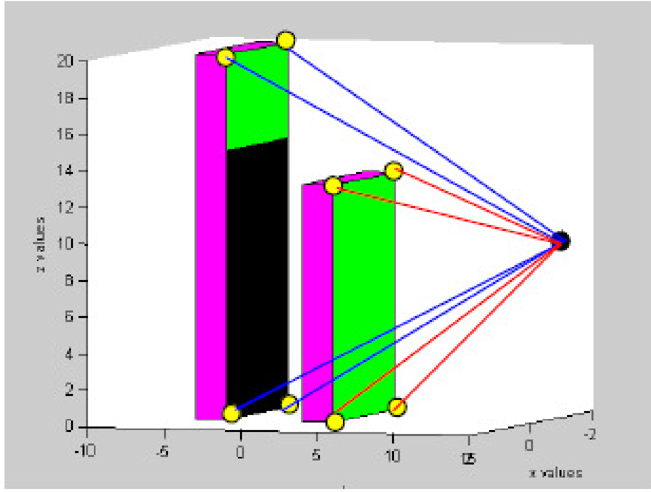
Hidden Surfaces - Demonstration



(a)



(b)

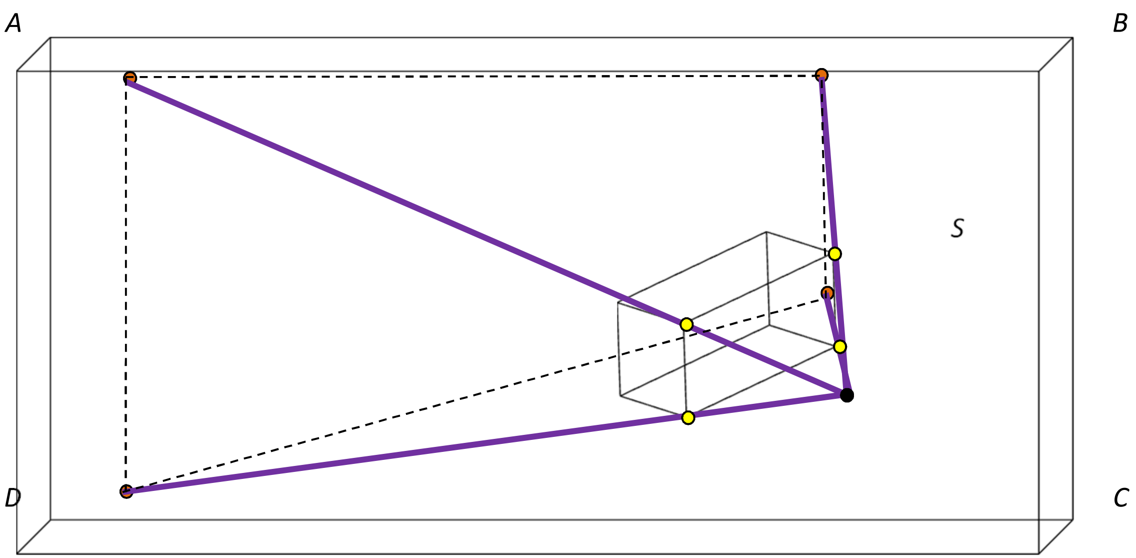


(c)

Generating VP – (a) VP_1^1 boundary colored in red arrows; (b) VP_2^1 boundary colored in blue lines; (c) the two buildings - VP_1^1 in red and VP_2^1 in blue, from the viewpoint.

Projected Visibility Pyramid (PVP)

- **Projected Visible Pyramid (PVP)** - we define $PVP_i^j(x,y,z)$ of the object *i* as 3D projected points to the bounding volume *S*, VBP of $V(x_0, y_0, z_0)$ specific surface *j* trough viewpoint.



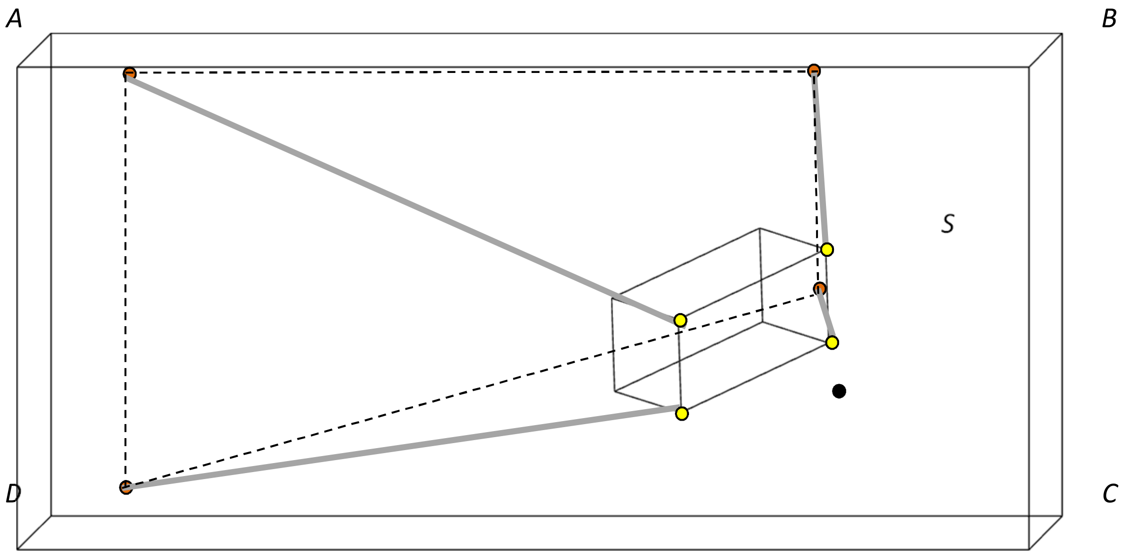
Projected Visible Pyramid Boundaries colored with purple arrows from a Viewpoint (marked as a Black Dot) to the boundary surface *ABCD* of Bounding Volume *S*.

3D Visible & Invisible Volumes

- **The 3D Visible Volumes inside bounding volume *S*, VV_s, computed as the total bounding volume *S*, V_s minus the Invisible Volumes, IV_s .**

$$VV_S = V_S - \sum_{i=1}^{N_{obj}} \sum_{j=1}^{N_{surf}} IV_{S_i}^{j}$$

$$VV_S = V_S - \sum_{i=1}^{N_{obj}} \sum_{j=1}^{N_{surf}} \left(V(PVP_i^j) - V(VP_i^j)\right)$$

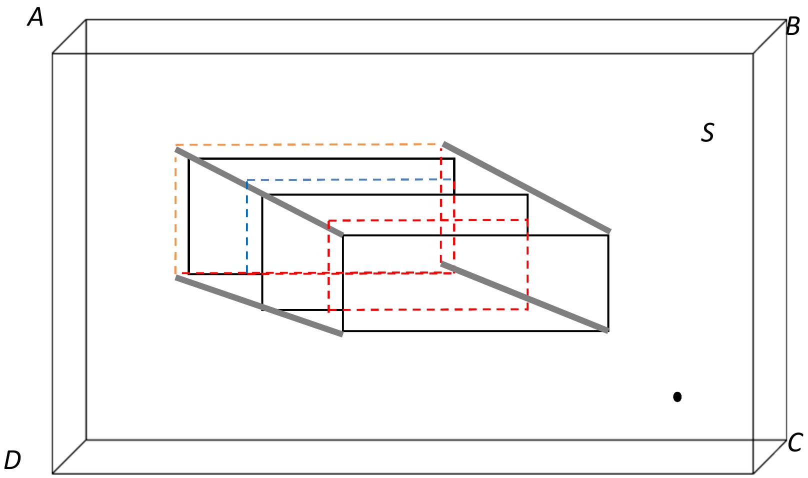


Invisible Volume Colored in Gray Arrows. Decreasing Projected Visible Pyramid boundary surface *ABCD* of Bounding Volume *S* from Visible Pyramid.

Invisible Hidden Volumes (IHV)

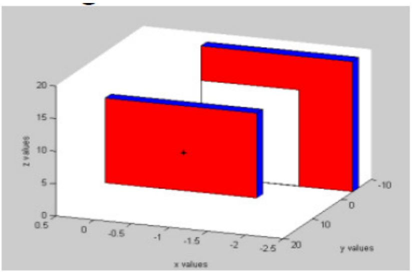
- **Invisible Hidden Volume (IHV)** - We define *Invisible Hidden Volume (IHV)*, as the Invisible Surface (IS) between visible pyramids projected to bounding box *S.*
- **In case of overlap objects, 3D visible volumes can be described as:**

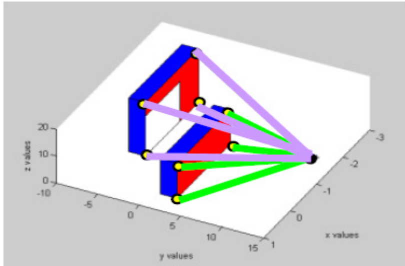
$$VV_S = V_S - \sum_{i=1}^{N_{obj}} \sum_{j=1}^{N_{surf}} (V(PVP_i^j) - V(VP_i^j) + IHV_i^j)$$

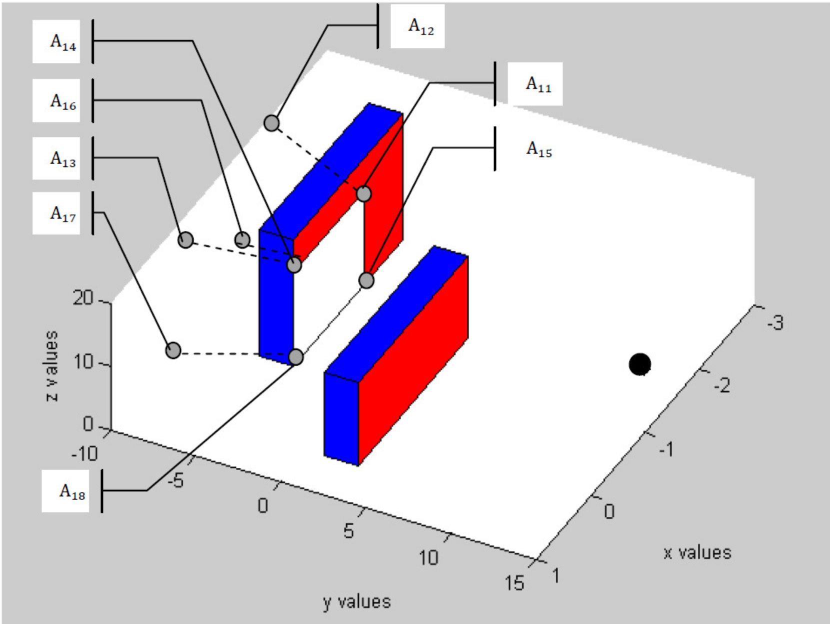


Three overlapping buildings. Invisible surfaces bounded with dotted lines, projected visible surfaces of the overlap building colored in gray.

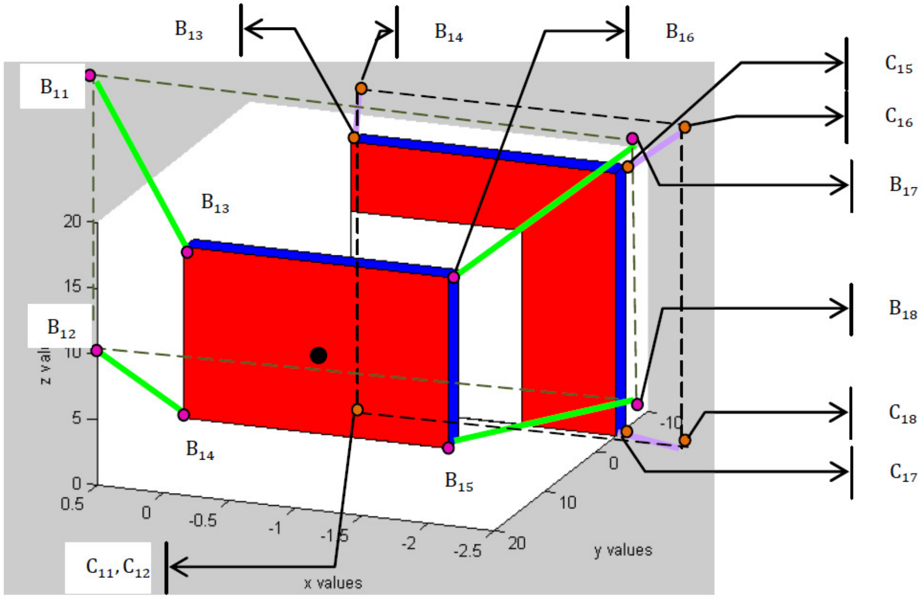
Overlapping Objects – *IHV & IV*







IHV boundary points colored with gray circles denoted.



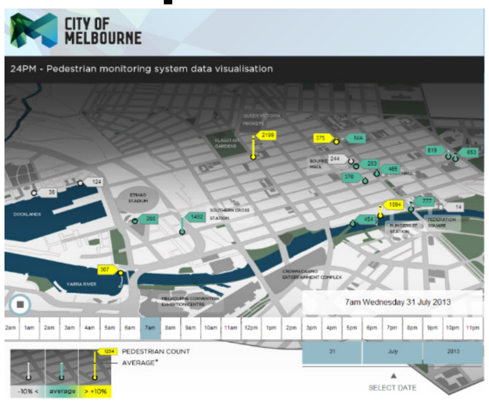
Invisible Volume colored in purple and green arrows for each building. *PVP* of the object close to viewpoint colored in black, colored with pink circles and the far object *PVP* colored with orange circle

Simulations

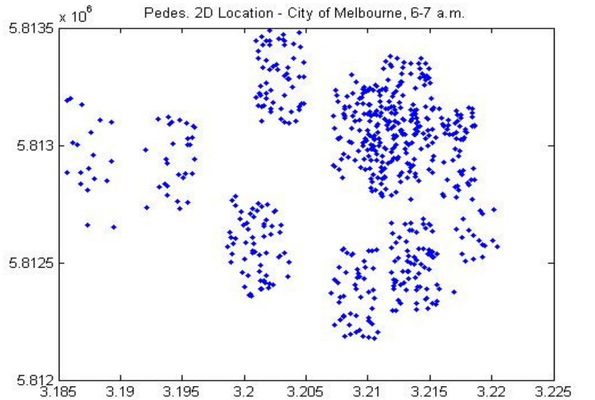
- we demonstrate the SVC method of estimating the number of clusters based on pedestrians' mobility datasets
- Our datasets are based on the city of Melbourne's 24-hour pedestrian monitoring system (24PM).
- Based on SVC method we've tested the following:
  - Estimating number of clusters from one to ten, per day hour.
  - Location of optimal control points during day hour using K-Means.
  - Time zones analysis for efficient pedestrian monitoring during a full month.

Our Datasets

- This system measures pedestrian activity at several Points of Interests (POI) with counting sensors.
- Our datasets include the number of pedestrians in each hour during July 2013, where POI defined as observation points.
- we approximated the pedestrians' location using kinematic model for pedestrians presented by *Hoogendoorn et al*.



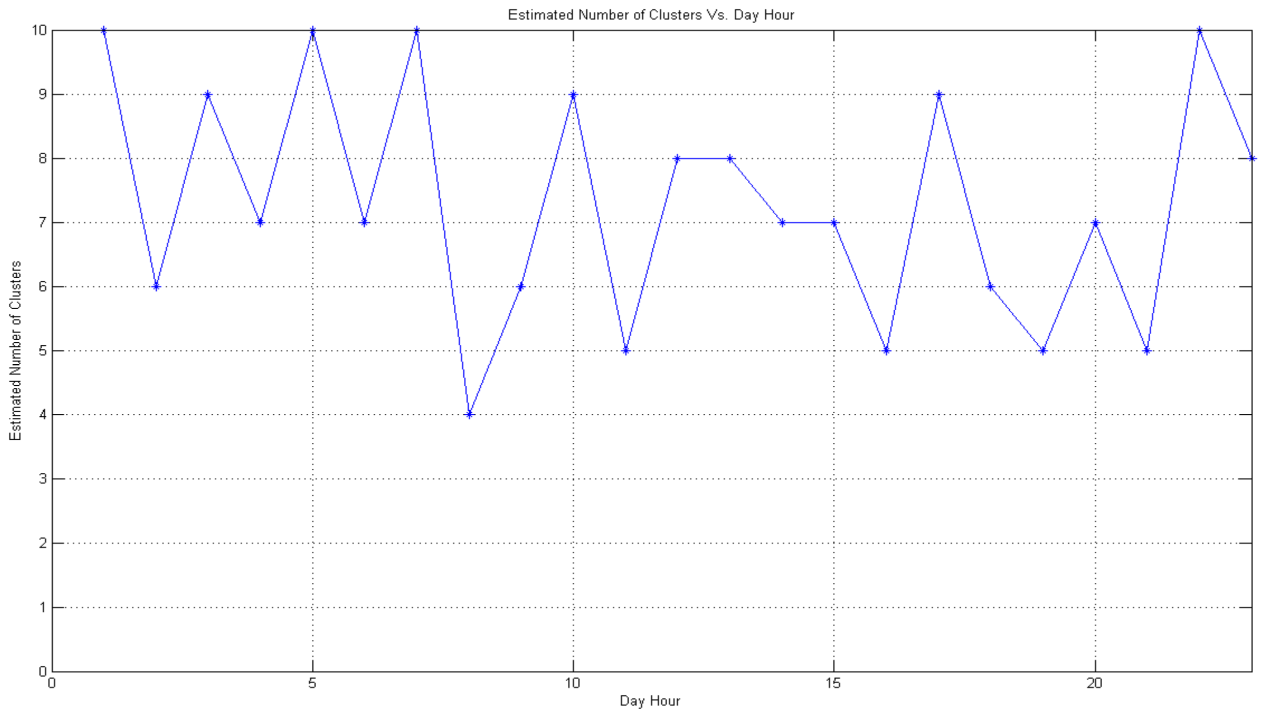
City of Melbourne's 24-hour pedestrian monitoring system (24PM) – Online Visualization Map.



Pedestrians' 2D estimated location using the Hoogendoorn model etc. between 6-7 a.m.

Estimating Number of Clusters

- At each POI, we set the reference dataset of the pedestrian location distributed uniformly around the POI location.
- The reference dataset size is the same one as the original dataset for the same POI, computing T_k^*.

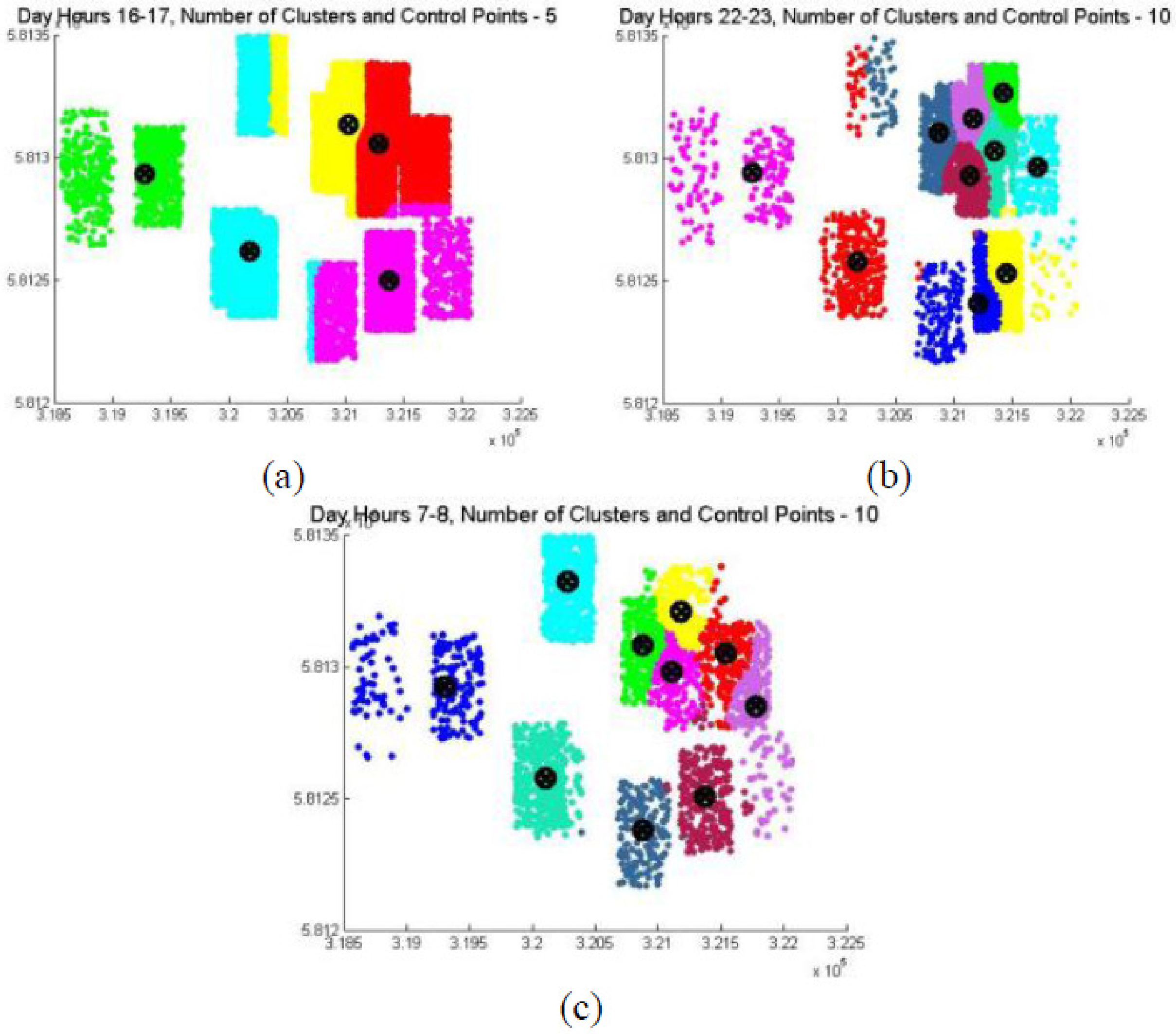


Number of Clusters for each Hour of 2/7/2013 Using SVC

Setting Optimal Control Points

- Based on SVC outcome, we set control points using K-means clustering method.
- This method produces exactly *k* different clusters, where *k* is predefined from the SVC method.
- The centroid of all objects in each cluster is set as control point.

Setting Optimal Control Points

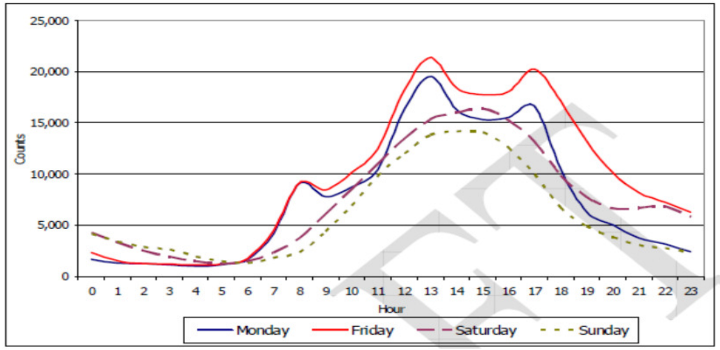


Control Points Location and Clusters Presentation during Each Hour in a Day.
Control points are marked with black circles. Pedestrians' mobility Clustered in different colors

Setting Optimal Control Points - Video

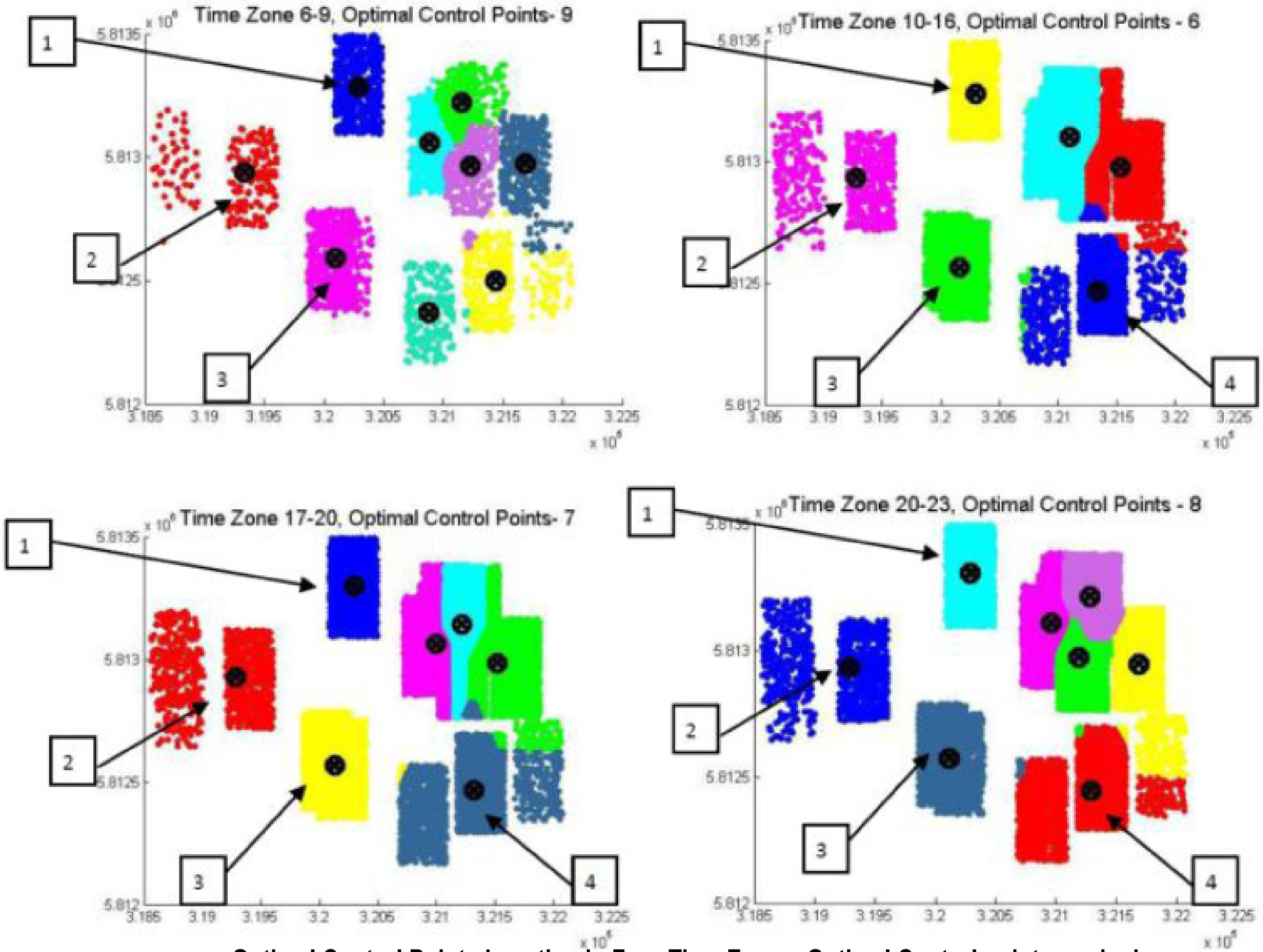
Time Zones Analysis

- Based on control points analysis, we focused on pedestrians' patterns analysis.
- We tested a full month's (July 2013) dataset, analyzing each day for twenty-four hours.
- We divide the day into four time zones for efficient pedestrian monitoring:
  - 1. Morning hours (movement to work) – 6 - 9 AM.
  - 2. Mid-Day Hours (between morning and afternoon) – 10 a.m. to 16 PM.
  - 3. Afternoon hours (back from work and activity hours) – 17- 20 PM.
  - 4. Night hours 20 - 23 PM.



Pedestrian Activity Analysis

Time Zones Analysis



Optimal Control Points Location in Four Time Zones. Optimal Control points marked with black circles. Pedestrians' mobility Clustered in different colors.

Conclusions

- We presented unified spatial analysis defining the number of clusters in a dataset based on analytic visibility analysis, SVC.
- Fast and exact 3D visible volumes analysis.
- We demonstrated the SVC by using datasets from the city of Melbourne's 24-hour pedestrian monitoring system (24PM).
- we analyzed pedestrian's mobility behavior, setting control points during a day's hours and dividing a day's hours into four time zones
- We found a correlation of several optimal control points in different time zones.
- The outcome of optimal control points can be used for various applications, such as entertainment, monitoring crowds‘ pedestrians in emergencies equipped with medical assistance.

Thank You