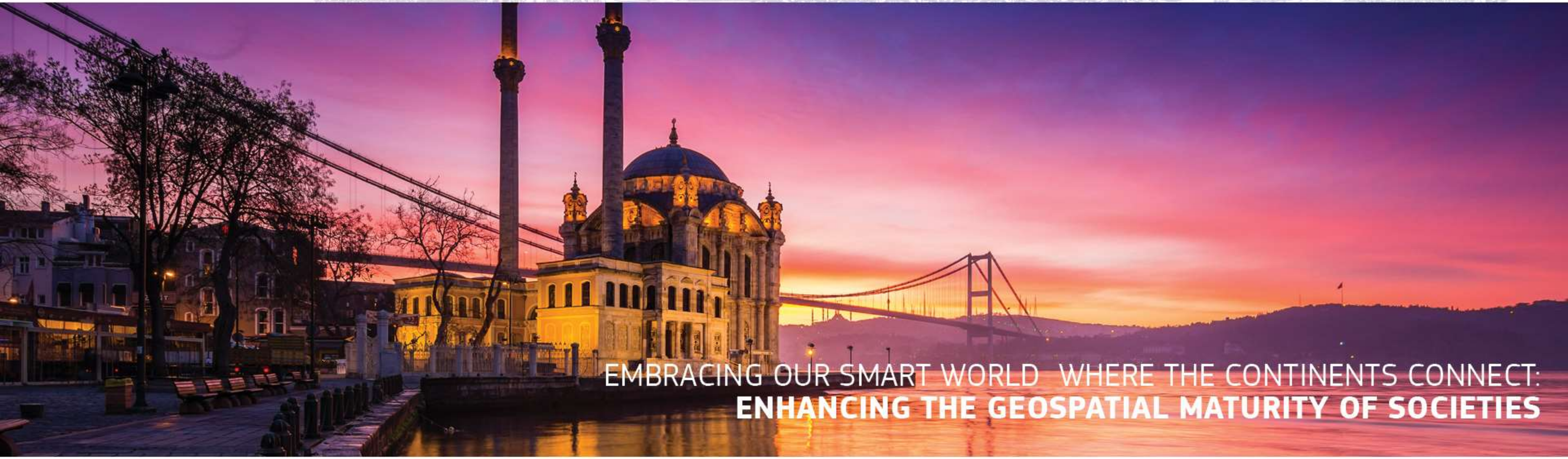
FIG 2018 ISTANBUL

XXVI FIG CONGRESS

6–11 May 2018, İstanbul



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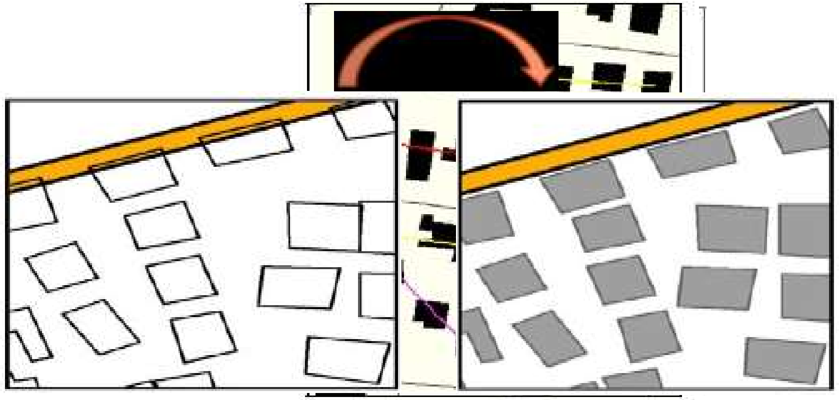
What is generalization?

The process of reducing the amount of detail in a map (or database) in a meaningful way

Building Generalization is a complex problem!

- Building clustering
- Building pattern detection
- Generalization (Rule-based generalization and spatial conflict reduction)

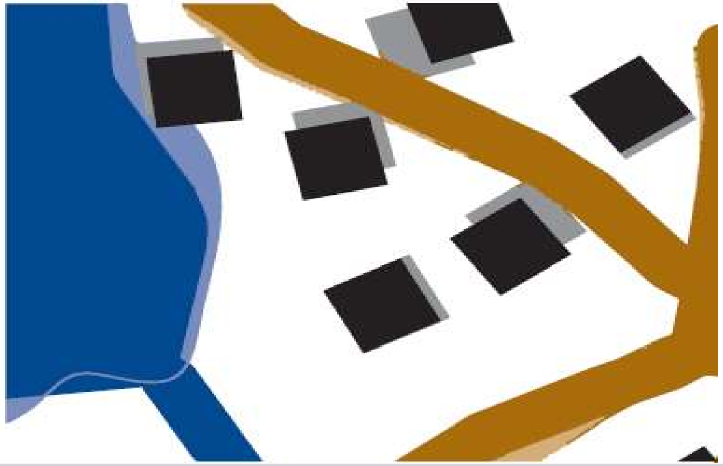


Why spatial conflict occur?

- when the distance between map objects is shorter than a minimum separable distance.
- when objects overlap each other.

How to resolve spatial conflicts?

- Aggregation
- Deletion
- Simplification
- Displacement
- …



Types of displacement algorithms

- **Sequential:** solve the conflicts one by one
- **Global** : displacements are considered as a global process

Optimization techniques

- **GA**
- **SA**
- **PSO**
- **IGA**
- **…**

- How effective are these algorithms in reducing the number of spatial conflicts?
- How effective are these algorithms in reducing the total displacement distance?
- How effective are these algorithms in the process of building generalization in terms of accuracy?

Building generalization process

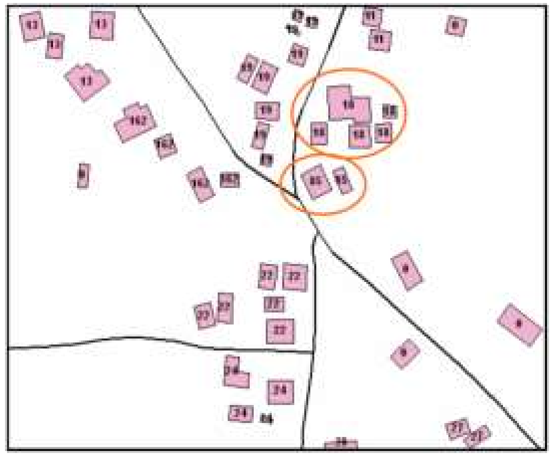
1. Building clustering

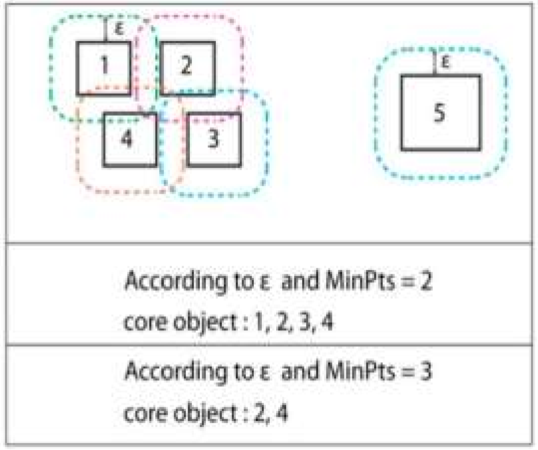
An imprortant task prior to building genealization operations

⬇

Building clustering using DBSCAN algorithm

It is a density-based algorithm with two global parameters, epsilon (eps) and minimum points (minPts).





Building generalization process

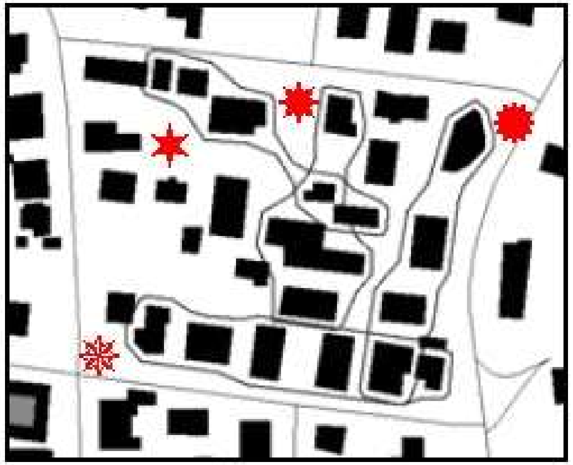
2. Building pattern detection

Arrangements that groups of buildings exhibit collectively in space

Different types of building patterns

- Align along roads
- Curvilinear
- Grid
- Collinear

Using Gestalt theory



Building generalization process

3. Generalization

3.1 Rule-based generalization

Operators for collinear patterns	Operators for buildings without pattern
1) If (the mean area of the building is > 625 m^2) and (the mean distance between buildings in the pattern < 25 m), Then the operator is **aggregation**.	1)If (building is a noise object) and (area of the building ≤ 625 m^2), Then the operator is **elimination**; otherwise
	2)If (building is a noise object) and (area of the building > 625 m^2), Then the operator is **simplification**; otherwise
	3)If (building belongs to a cluster) and (area of the building is ≤ 625 m^2) and (there is no building object within 25 m of that building), Then the operator is **elimination**; otherwise
2) The second operator is **simplification**.	4)If (building belongs to a cluster) and (are of the building is > 625 m^2) and (there are buildings within 25 m of that building), Then the operator is **aggregation**.
	5)The final operator is **simplification**.

Building generalization process

3. Generalization

3.1 Spatial conflict reduction

Feature symbolization may create spatial conflicts

1) Polygon – polygon
2) Polygon – road

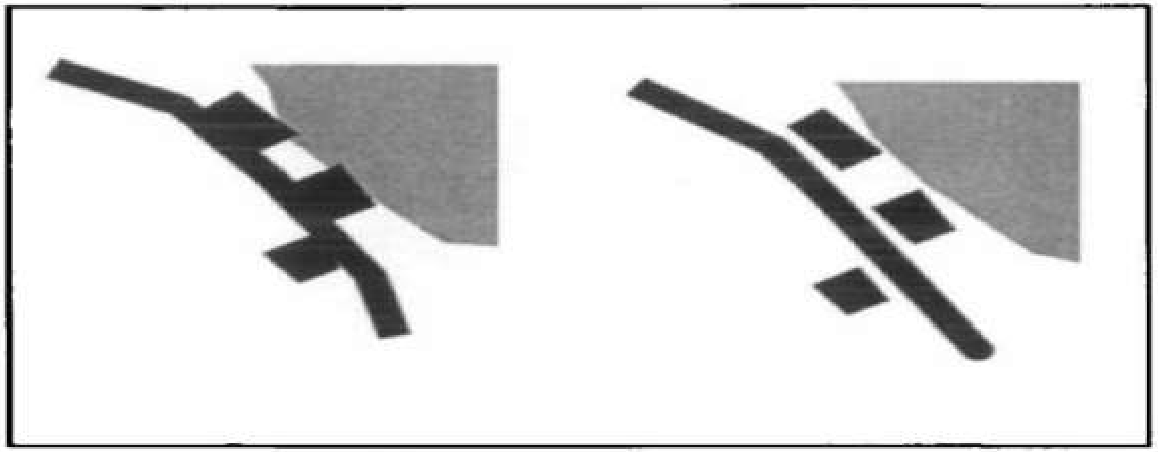
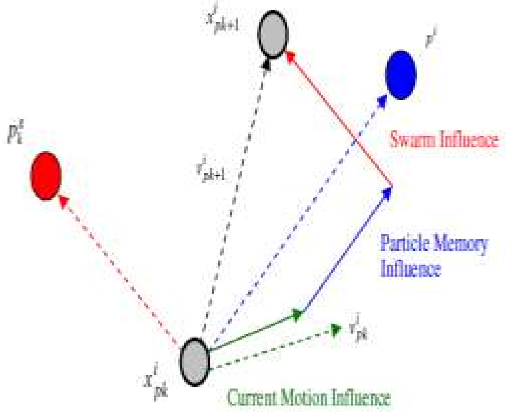


Figure 1. Before and after displacement.

Building generalization process

3. Spatial conflict reduction : PSO

- Uses a number of particles that constitute a swarm moving around in the search space looking for the best solution
- Each particle in search space adjusts its “flying” according to its own flying experience as well as the flying experience of other particles



Building generalization process

3. Spatial conflict reduction : SA

- SA algorithm attempts to overcome the problem of getting caught in local minima by sometimes allowing non-improving solutioms to be accepted.
- SA always accepts new state if it offers a better solution than current state. However, in cases where new state provides no improvement, SA will accept the new solution with some probability.

Building generalization process

3. Spatial conflict reduction : Objective function

$$f = ((f_1 w_1) + (f_2 w_2) + (f_3 w_3))$$

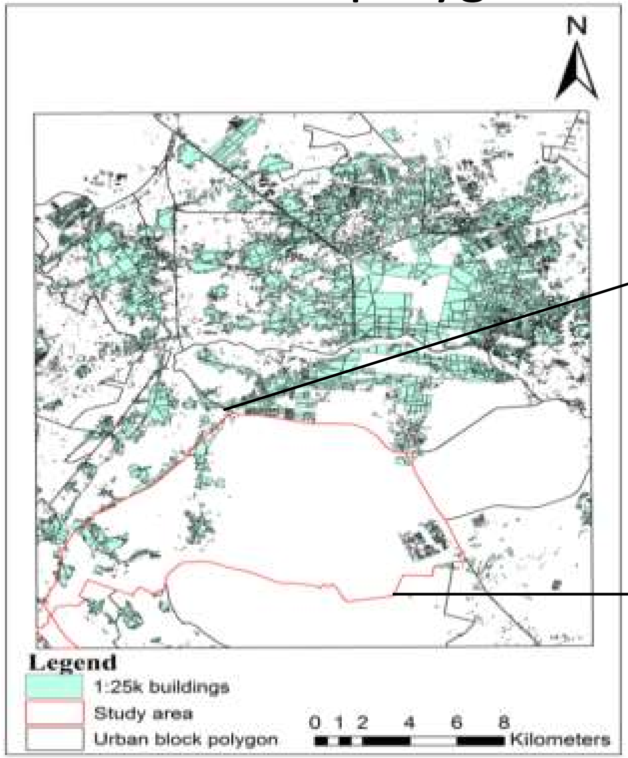
f_1: Number of polygon-polygon conflict

f_2: Number of polygon-road conflict

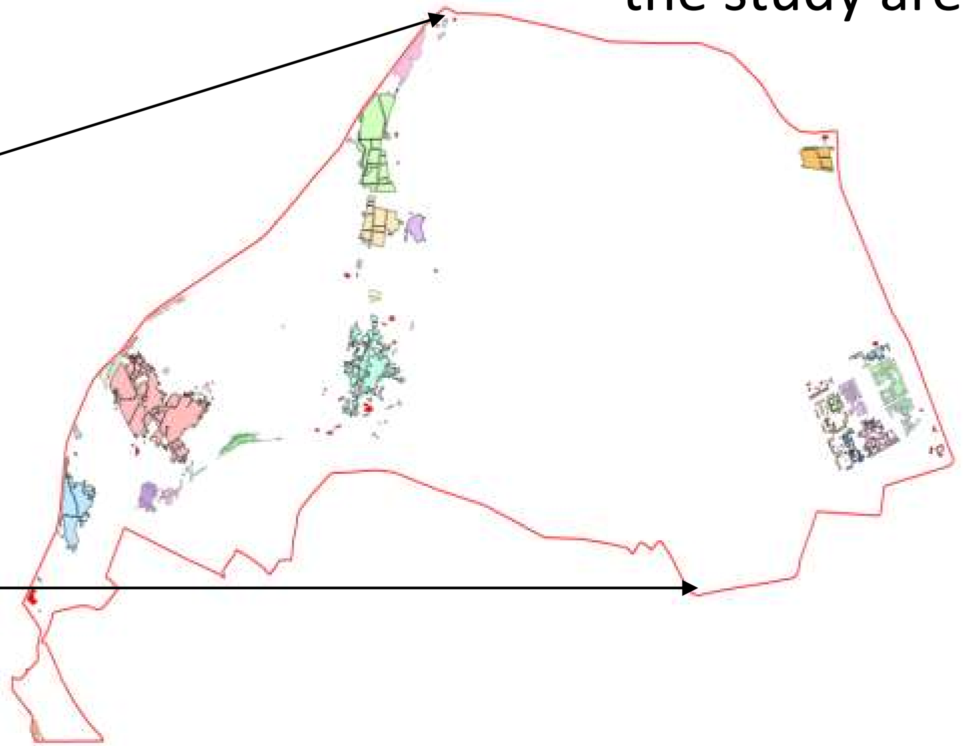
f_3: Sums the normalized, absolute, distance each polygon has been displaced and scaled from its original state

Study Area

Urban block polygons



The clustering results in the study area



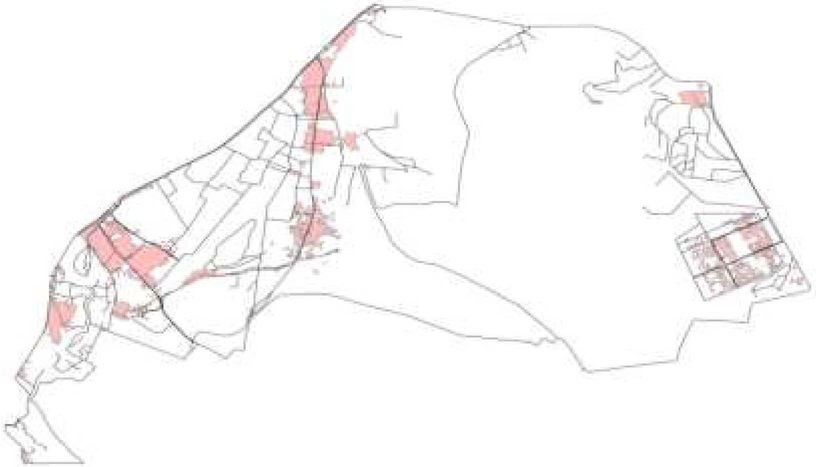
Input parameters of optimization algorithms

Algorithm	Parameter values
PSO	w=0.9, c_1=1.2 and c_2=2.3 (based on Huang et al., 2017)
SA	t=3.0 and $\gamma = 0.9$ (based on Ware et al., 2003)

The numerical indices of the displacement results

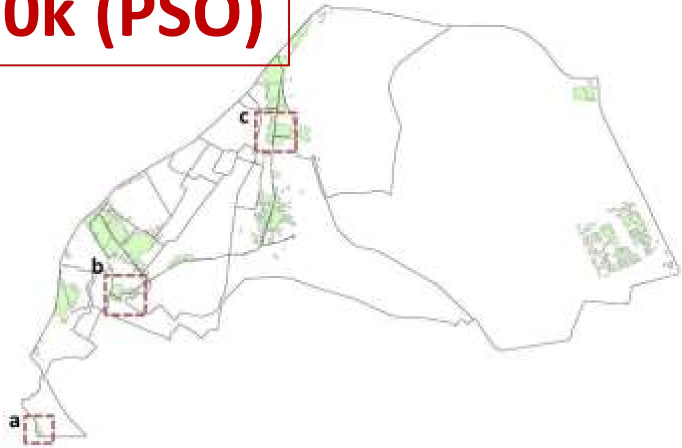
Optimization method	Number of initial conflicts	results of 10 iterations			results of 15 iterations			results of 20 iterations		
		final conflict	Total displacement (m)	final cost (f)	final conflict	Total displacement (m)	final cost (f)	final conflict	Total displacement (m)	final cost (f)
PSO	74	51	200.59	56.69	46	167.67	50.41	38	149.66	42.77
SA		55	202.85	59.80	50	190.76	55.83	44	179.30	51.88

- ❑ Introduction
- ❑ Material and Methods
- ☑ **Results and Discussions**
- ❑ Evaluation
- ❑ Conclusion

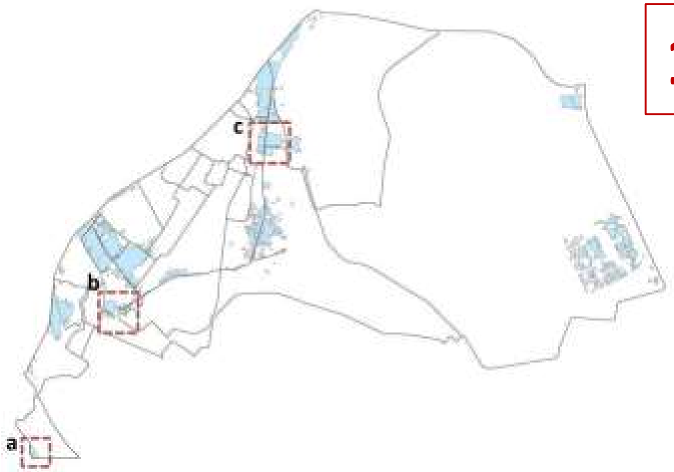


1:25k

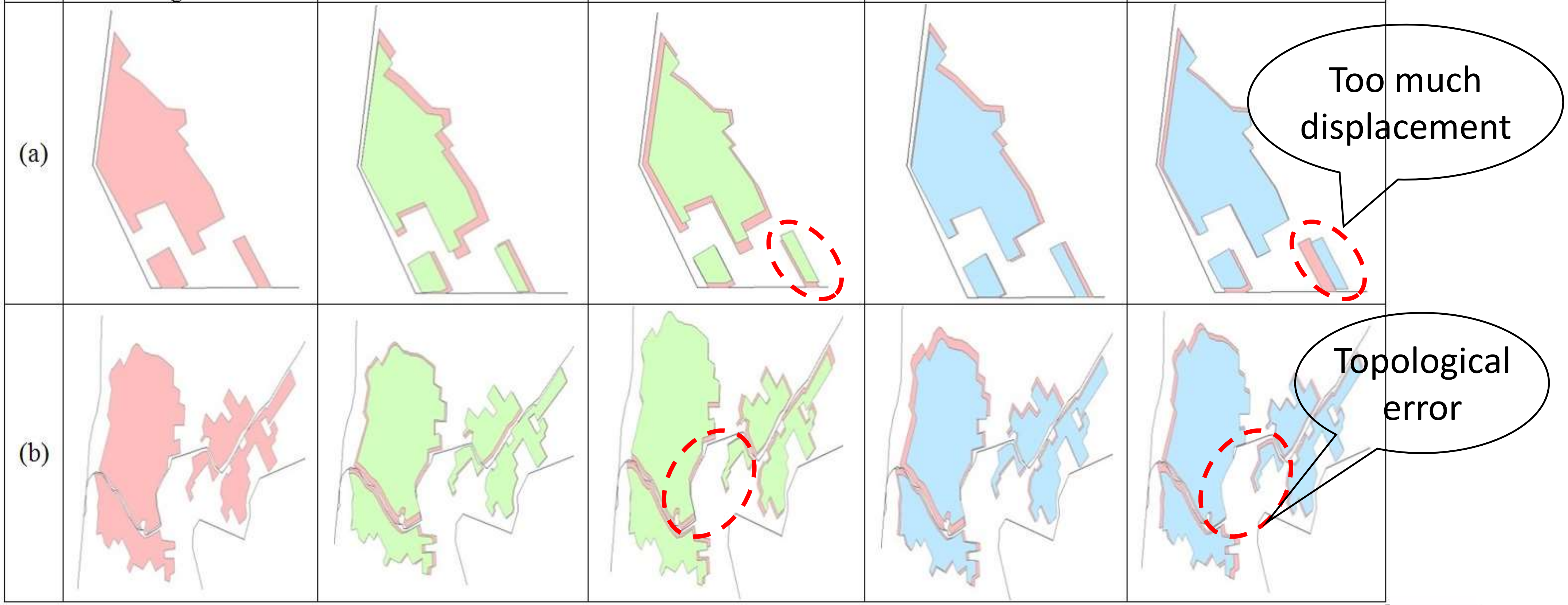
1:50k (PSO)



1:50k (SA)



	original buildings close to a road segment	PSO results		SA results	
		after 10 iterations	after 20 iterations	after 10 iterations	after 20 iterations



Comparing the results of harmony assessments with the result of manual generalization

state	No. of buildings	Ratio between the building area and the free space area (%)	Block density (%)	Mean of first nearest neighbor distance	SumDev
before generalization	478	5.56	5.27	46.05	-
SA after 10 iterations	279	5.28	5.02	47.15	1.63
SA after 15 iterations		5.28	5.02	46.73	1.21
SA after 20 iterations		5.32	5.05	46.69	1.10
PSO after 10 iterations	279	5.31	5.04	47.01	1.44
PSO after 15 iterations		5.32	5.05	46.78	1.19
PSO after 20 iterations		5.35	5.08	46.62	0.97

The accuracy assessment results in four generalized datasets based on PSO and SA

Optimization algorithm	After 10 iterations		After 15 iterations		After 20 iterations	
	Correctness (%)	Completeness (%)	Correctness (%)	Completeness (%)	Correctness (%)	Completeness (%)
PSO	60.21	60.23	61.89	62.54	65.29	65.75
SA	57.99	58.49	59.24	59.31	60.77	61.06

The PSO algorithm results in fewer spatial conflicts compared to SA algorithm

The PSO algorithm results in smaller movements compared to SA algorithm.

In terms of accuracy, the PSO algorithm is superior to SA algorithm

Thanks for your attention !

DBSCAN parameters

An object is defined as a core object if its neighbourhood of radius ε contains at least MinPts objects. A core object is arbitrarily selected to begin clustering process. The objects within ε-neighbourhood of the core object and itself constitute a cluster. All members of the cluster are scanned for finding another core objects. If found any, objects then within its ε-neighbourhood are added to the cluster and the scanning is resumed until all objects in the cluster are processed; otherwise a new core object that is not assigned into a cluster is selected to constitute a new cluster. This procedure continues until all core objects are assigned to a cluster.

PSO

- The particle swarm optimization (PSO) algorithm was first introduced by Kennedy and Eberhart (1995). The PSO algorithm regards a candidate solution for a problem as a particle. First, the algorithm initializes a swarm of particles. Each particle determines the beat solution. At the individual level, this is called the personal best solution. However, at the global level, this is called the global best solution. The personal best particle set contains all the particles' personal best positions which have minimum objective values, and the global best particle is the particle with the minimum objective value from the personal best set. Through information exchange among the personal best particles, the global best particle and all other particles, a final best solution is found. In PSO, each individual solution (particle) flies at a certain speed in the searching space. Its velocity is adjusted by considering its own and its companions' flight experiences and its position is upadated using its previous position and its current velocity.

SA

Simulated annealing (SA) algorithm attempts to overcome the problem of getting caught in local minima by sometimes allowing non-improving solutioms to be accepted. SA always accepts new state if it offers a better solution than current state. However, in cases where new state provides no improvement, SA will accept the new solution with some probability. At each iteration the probability P is dependant on two variables: ΔE (measured by the difference in objective value between the new and current states) and T (the current temperature) (Equation 4) (Ware et al., 2003):
The probability P is usually tested against a random number R (0<R<1). A value of R<P results in the new state being accepted. In Equation (4), T is assigned a relatively high initial value; its value decreases through running the algorithm. At high values of T poor displacements (large negative ΔE) will often be accepted. At low values of T poor displacements will tend to be rejected. Although displacements resulting in small negative ΔE might still sometimes be accepted to allow escape from locally optimal solutions.

$$f_3 = \sum_{i=1}^{n} \sqrt{dx_i^2} + \sqrt{dy_i^2} + dz_i$$

dx and dy are the distance an object has been displaced in the X and Y axis, respectively, and dz is the percentage an object is scaled.

SumDev

- SumDev, is the proposed by Li et al. (2004) as follows:
-
- $\mathrm{SumDev} = \sum \mathrm{abs}(\mathrm{i} - \mathrm{j})$
  -
- $\mathrm{abs}(\mathrm{k})$ is the absolute value of k, i is the desired information before generalization and j is the corresponding information after generalization. If $\mathrm{SumDev} = 0$ obviously the result is ideal; otherwise, the larger the SumDev, the worse the result.