Spatial conflict reduction in building generalization process using optimization approaches

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Key words: GIS, cartography, map generalization, spatial conflict, displacement.

SUMMARY

Building generalization represents an essential step in topographic map generalization. This process involves three main steps: Building clustering, building pattern detection and building generalization and spatial conflict reduction. This paper presents a comparative study of two optimization algorithms (particle swarm optimization (PSO) and simulated annealing (SA) algorithms) for spatial conflict reduction in building generalization process. The objective of this study is to analyze the algorithms considering three points. The first one is the reduction in total conflicts; the second one is the total displacement distance and the third one is their accuracy in the building generalization process. A real building dataset at 1:25k dcale is used to evaluate the algorithms in complete building generalization process. The success of the algorithms are evaluated firstly using the ratios between the building area and the free space area, block density and the mean of the first nearest neighbor distances in the block, before and after the generalization and secondly by comparing the generalized results with those produced manually by cartographer. The results demonstrated that both approaches are successful in reducing spatial conflict. In other words, with the increase in the number of iterations, the number of conflicts and total displacement distances are decreased for both algorithm, while the accuracy of the final map increases. However, when compared against each other, the PSO algorithm is superior regarding the fewer number of total conflicts, smaller total displacement distance and higher accuracy in the generalization process. Therefore, it can be concluded that the quality of the result is better when the spatial conflicts problem is solved using PSO algorithm. So, it is beneficial for the building generalization process.

SUMMARY

جنرالیزاسیون ساختمان‌ها یک گام اساسی در جنرالیزاسیون نقشه‌های توپوگرافی می‌باشد. این فرایند شامل سه مرحله اصلی می‌باشد: گروه بندی ساختمان‌ها، شناسایی الگوهای ساختمان‌ها و جنرالیزاسیون ساختمان‌ها و رفع تضاد مکانی آن‌ها. این مقاله به بررسی مقایسه‌ای دو الگوریتم بهینه سازی (الگوریتم بهینه سازی ازدحام ذرات (PSO) و تبرید شبیه سازی شده (SA)) برای کاهش تضاد مکانی در فرایند جنرالیزاسیون ساختمان‌ها می‌پردازد. هدف از این مطالعه، بررسی این الگوریتم‌ها با در نظر گرفتن سه موضوع می‌باشد. یکی از این موارد کاهش تضاد مکانی می‌باشد، دومین مورد کل فاصله جابجایی می‌باشد و سومین مورد، دقت آن‌ها در فرایند جنرالیزاسیون ساختمان‌ها می‌باشد. یک مجموعه داده واقعی در مقیاس 1:25.000 برای ارزیابی الگوریتم‌ها در فرایند جنرالیزاسیون ساختمان‌ها استفاده شده است. موفقیت الگوریتم‌ها ابتدا با استفاده از نسبت بین مساحت ساختمان‌ها و مساحت فضای آزاد، تراکم بلوک و میانگین اولین فاصله نزدیک‌ترین

همسایگی در بلوک قبل و بعد از جنرالیزاسیون و سپس، با استفاده از مقایسه نتایج جنرالیزاسیون با نتایج تولید شده به صورت دستی توسط کارتوگراف، ارزیابی شد. نتایج نشان دادند که هر دو روش در کاهش تضاد مکانی در فرایند جنرالیزاسیون ساختمان‌ها موفق هستند. به عبارت دیگر، با افزایش تعداد تکرارها، تعداد تضادها و فاصله جابجایی برای دو الگوریتم کاهش پیدا کرده در حالی که دقت نقشه نهایی افزایش پیدا کرده است. با این وجود در مقایسه با یکدیگر، الگوریتم PSO با توجه به تعداد کمتر تضادهای مکانی، جابجایی کل کمتر و دقت بیشتر در فرایند جنرالیزاسیون، برتر می‌باشد. بنابراین می‌توان نتیجه گرفت که هنگامی که مسئله تضاد مکانی با استفاده از الگوریتم PSO حل می‌شود، کیفیت نتایج بهتر است. بنابراین، این روش برای فرایند جنرالیزاسیون ساختمان‌ها سودمند می‌باشد.

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1. INTRODUCTION

Map generalization is a complex procedure for producing small-scale maps from large-scale maps using various appropriate operations (Steiniger and Weibel 2007; Renard and Duchene 2014; Deng et al., 2017). Building generalization represents an essential step in topographic map generalization (Basaraner and Selcuk 2008; Ai et al. 2015). This process involves three main steps. First, a spatial clustering algorithm is applied to the dataset. Second, spatial patterns in different clusters are detected (Li et al. 2004; Harrie and Weibel 2007). Third, the created clusters and patterns will be used for determining generalization operators and also, the spatial conflicts are removed to guarantee map legibility (Sun et al. 2016).

Spatial conflicts occur when the distance between map objects (e.g., between buildings or between a building and other features, such as roads) is shorter than a minimum separable distance that the human visual system can identify, or when objects overlap each other. Such conflicts usually make the map less readable (Ware et al., 2003; Ai et al., 2015). To resolve such conflicts, displacement is the most frequently used operator in a map production environment (Wilson et al., 2003; Ai et al., 2015). A successful displacement should address two main issues. First, it should resolve multiple conflicts simultaneously and avoid generating secondary conflicts after the displacement (Wilson et al., 2003; Ai et al., 2015). The purpose of an optimal displacement algorithm is to search for a candidate displacement solution with minimal or no conflict (Huang et al., 2017). Due to the important role that the displacement operator plays during building generalization, this paper has focused on displacement for solving spatial conflict problem.

Displacement algorithms are basically divided into two groups, i.e. sequential or global. In the context of sequential approaches, Ruas (1998) proposed an approach to displace buildings sequentially. However, due to the complexity and limitations of sequential approaches, global approaches such as optimization methods were developed. In global methods, displacements are considered as a global process, rather than being computed and triggered sequentially. This includes the displacement using the finite element method (FEM) (Højholt 2000), the least-squares adjustment in building simplification and displacement (Sester 2000, Harrie and Sarjakoski 2002), simulated annealing (SA) (Ware et al. 2003), genetic algorithm (Wilson et al, 2003), elastic beam-based method (Bader et al. 2005), Vector field model (Ai et al., 2015), immune genetic algorithm (IGA) (Sun et al., 2016) and improved particle swarm optimization algorithm (Huang et al., 2017).

According to the previous literature, optimization algorithms are usually employed to resolve spatial conflicts under different contexts. Therefore, this study focuses on the comparative analysis and assessment of two optimization algorithms for spatial conflict reduction in building generalization process, i.e., PSO and SA algorithms. In particular, the objective of this study is to evaluate the algorithms considering three points: one is the reduction in total conflicts, the other is the total displacement distance and the third one is their accuracy in the generalization process. Therefore, the objetive of this study is to answer the following questions:

1) How effective are these algorithms in reducing the number of spatial conflicts?

2) How effective are these algorithms in reducing the total displacement distance?

3) How effective are these algorithms in the process of building generalization in terms of accuracy?

The remainder of the paper is organized as follows: Section 2 describes briefly the complete building generalization process in section 2.1 and describes the concepts of PSO and SA algorithms in section 2.2. The results are presented in section 3 and evaluated in section 4. The last section (section 5) presents conclusions and future work directions.

2. MATERIAL AND METHODS

This section is divided into two parts. In the first part (section 2.1) the complete building generalization process is shortly described. On the other hand, since the focus of this paper is on spatial conflict reduction, the PSO and SA approaches for the reduction of spatial conflicts and their objective function are explained in section 2.2.

2.1 Building generalization process

As mentioned in the introduction, building generalization process includes three main steps, i.e., building clustering (section 2.1.1), building pattern detection (section 2.1.2) and building generalization (section 2.1.3) which are briefly described in the following.

2.1.1 Building clustering

Building clustering is an important task prior to building generalization operations (Yan et al. 2008; Liqiang et al. 2013). In this paper we have performed building clustering using DBSCAN algorithm. It is a density-based algorithm with two global parameters, epsilon (eps) and minimum points (minPts). According to Ester et al. (1996) eps is determined globally using the interactive k-NN distance graph and the parameter minPts is set to k. Full definitions and details can be found in Ester et al. (1996).

It should be noted that since the objects on a map are too big to be dealt with at once, it is necessary to divide map into different work spaces using transportation networks (Sun et al., 2016). So, before clustering, partitioning of buildings on the whole map is performed by means of main road networks, by which urban block polygons are formed. Also, since roads have a higher priority than buildings in map generalization, only after roads are generalized can the global partitioning of buildings in the same area be calculated correctly.

Building pattern detection

Building patterns refer to the arrangements and forms that groups of buildings exhibit collectively in space, which can be recognized visually and named semantically (Du et al., 2016a). Usually Gestalt criteria (Wertheimer, 1923) have been applied for the pattern extraction (Li et al., 2004; Gong and Wu, 2016; Deng et al., 2017). For the detection of building patterns these criteria include proximity, size similarity, common region and common orientation (Zhang et al., 2013).

Among all types of building patterns, collinear patterns are among the common distributions and are the foundation for extracting other types of patterns. Also they are essential elements in determining generalization operators. So, in this paper, collinear patterns of each cluster are extracted using the criteria described in Du et al. (2016a), i.e., the overall similarity and building arrangements criteria (Equation (1)).

$$\text{Collinear Pattern }(\mathrm{A},\mathrm{B}) = \begin{cases} \mathrm{Sim}_{\mathrm{total}}(\mathrm{A},\mathrm{B}) > \varepsilon_{\mathrm{sim}} \\ \mathrm{E}_{Arrange}(\mathrm{A},\mathrm{B}) < \delta \end{cases} \tag{1}$$

Where, ε_{sim} and δ are the thresholds of total similarity and building arrangements, respectively. Total similarity is the weighted combination of area, rectangularity, length-width ratio and distance similarities. For the computation of building arrangements, we have considered the difference between the main directions of two buildings for the sake of simplicity.

2.1.2 Building generalization

For building generalization, we used the existing guidelines and determined different generalization rules for buildings with collinear patterns and buildings without pattern using aggregation, simplification and elimination operations. So, in this way, the representative patterns and distributions are maintained. The rules are described in Table 1.

Table 1. Selection of appropriate generalization operator

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.

After generalization, symbols are assigned to roads. Road symbolization may create spatial conflicts between roads and neighboring buildings. A primary operator to resolve spatial conflicts is displacement operator (Ware et al., 2003; Wilson et al., 2003; Ai et al., 2015; Huang et al., 2017). In this paper we employed PSO and SA algorithms with the continuous solution space for the reduction of conflicts which are described in section 2.2.

2.2 Spatial conflict reduction

One of the main constraints in building generalization is to resolve spatial conflicts (Ai et al., 2015). In the following the PSO and SA algorithms are explained in section 2.2.1 and 2.2.2, respectively. Finally, in section 2.2.3, the objective function which is used for the two algorithms is presented.

2.2.1 Particle swarm optimization algorithm

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 (Equation 2). And its position is upadated using Equation (3) (Huang et al., 2017).

$$v_{in}^{k+1} = w \times v_{in}^{k} + c_1 \times r_1 \times \left(p_{in}^{k} - x_{in}^{k}\right) + c_2 \times r_2 \times (p_{gn}^{k} - x_{in}^{k}) \tag{2}$$

$$x_{in}^{k+1} = x_{in}^{k} + v_{in}^{k+1} \tag{3}$$

where x_{in}^{k} denotes the i-th particle's position in the n-th dimension at the k-th iteration, and v_{in}^{k} denotes the i-th particles' velocity in the n-th dimension at the k-th iteration. Here, p_{in}^{k} represents the i-th particle's best position in the n-th dimension, and p_{gn}^{k} represents the best position of the entire particle group in the n-th dimension. The parameters w, c_1, and c_2 are constants, and r_1 and r_2 are random numbers between 0 and 1. In Equation (2), the inertia weight w is used to determine how much of the particles' previous velocity is preserved; a larger inertia weight indicates that the search is more global, while a smaller inertia weight indicates a local search. In our study, the n-th dimension means the n-th building polygon.

2.2.2 Simulated annealing algorithm

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):

$$p = e^{\frac{-\Delta E}{T}} \tag{4}$$

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.

The initial value of T and the rate by which it decreases is governed by the annealing schedule. In this paper, we employed the same SA implementation used by Ware et al. (2003) for building displacement but instead of trial position approach, we have considered continuous solution space. For the annealing schedule, at each iteration, T is decreased such that $T_{new} = \gamma T_{old}$. More details can be found in Ware et al. (2003).

2.2.3 Objective function

The success of any optimization algorithm depends on its objective function, which is a measurement that evaluates the quality of any given element of the search space (a map realization in our case) (Ware et al., 2003; Huang et al., 2017). The objective function used in this paper considers two categories of spatial conflict (polygon-polygon conflict and polygon - road conflict) and also the degree to which an object has been displaced and scaled from its original state the same as the one used by Wilson et al. (2003) (Equation 5):

$$f = ((f_1 w_1) + (f_2 w_2) + (f_3 w_3)) \quad (5)$$

Where, f_1, represents the number of polygons that conflict with each other, f_2 represents the number of polygons that conflict with roads and f_3, sums the normalized, absolute, distance each polygon has been displaced and scaled from its original state (Equation 6). The parameters w_i represent the weight of each particular measure with a low value of f indicating a good solution.

$$f_3 = \sum_{i=1}^{n} \sqrt{dx_i^2} + \sqrt{dy_i^2} + dz_i \quad (6)$$

In Equation (6), 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 reduced.

3. RESULTS AND DISCUSSIONS

In this study, a real building dataset at scale of 1: 25k from topographic database of Isfahan province, Iran is used in the experiments (Figure 1). This dataset is obtained from the National Cartographic Center (NCC) of Iran. All the methods are coded in C# using Visual Studio 2012 (.NET Framework 3.5). It should be noted that the target scale for this paper is 1:50k. In the following the result are presented.

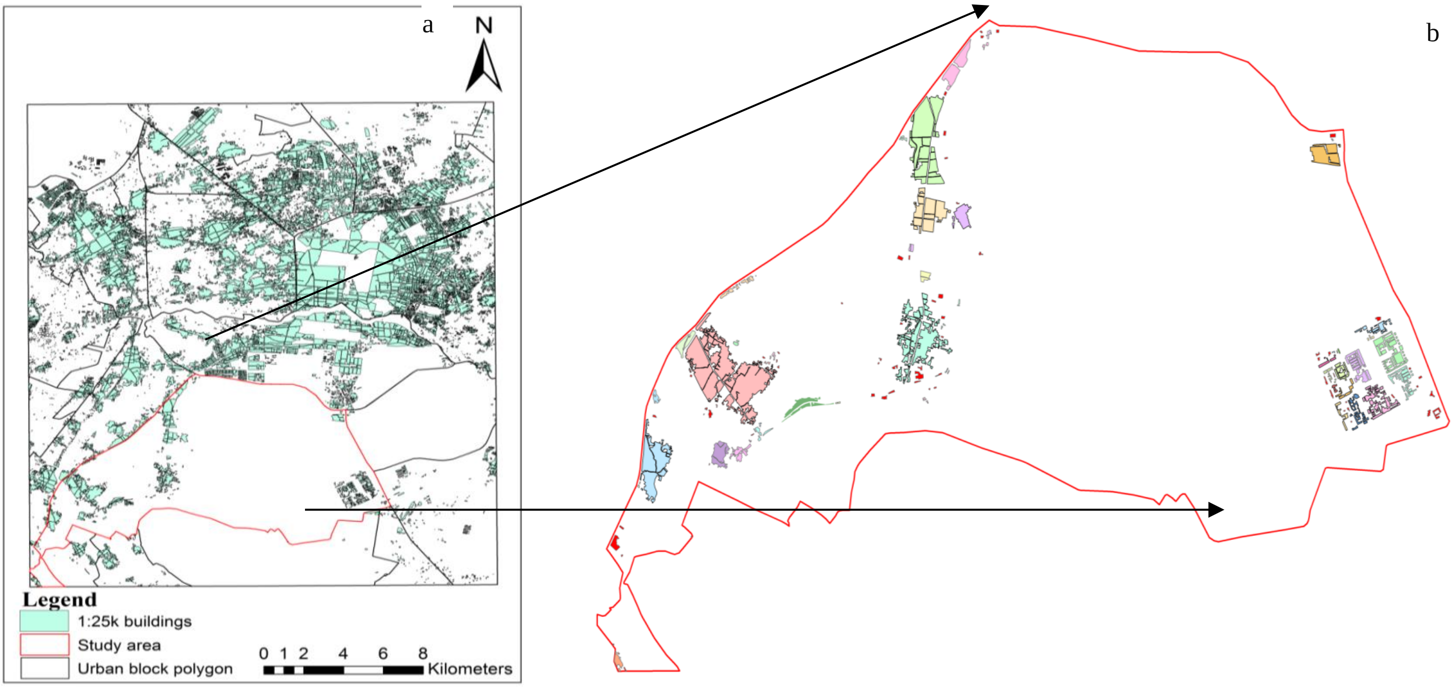

Figure 1. Urban block polygons and the study area (a), the clustering result in the study area (b).

In the first stage of implementation, roads are generalized using selection, simplification, deletion and in some cases smoothing operations. After that, urban block polygons are created using the generalized main road networks. This results in 24 urban block polygons (Figure 1a). After that, one urban block containing 478 buildings is selected for applying the model (Figure 1a). After creating urban blocks, block-based proximity matrices are computed as the input of DBSCAN algorithm. Then, for DBSCAN parameters, minPts is eliminated by setting it to 2 and eps is determined using the interactive 2-NN (k=2) distance graph as 20m. To show the results of clustering we visualize each cluster by a different color (Figure 1b). The DBSCAN algorithm generated 48 clusters for the selected dataset.

After building clustering, collinear patterns of the clusters are determined. According to Du et al. (2016a), the thresholds of total similarity and direction difference are set to 0.85 and 10, and the weights of area, rectangularity, length-width ratio and distance similarities are set to 0.230, 0.332, 0.217 and 0.221, respectively.

After that, the buildings are generalized using generalization operators determined for each group/pattern (Table 1). It should be noted that in this step, the generalized road network is considered as constraint. Finally, using the buildings' original positions as the initial positions, PSO and SA algorithms are applied to the selected block in order to reduce the spatial conflicts. The minimum separating distance tolerances used assume a visual perception threshold of 0.15 mm and the values of w_1, w_2 and w_3 for the objective function were set to 0.3, 0.6 and 0.1, respectively. For both algorithms, the population size and number of iterations are set to 10 and 20, respectively. Other input parameters of the algorithms are provided in Table 2.

Table 2. 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 are pretented in Table 3. The results demonstrated that both approaches are successful in reducing spatial conflict. In other words, with the increase in the number of iterations, the number of conflicts and total dispalcement distancs are decreased for both algorithm. However, when compared against each other, the PSO algorithm is superior regarding the fewer number of total conflicts and smaller total dispalcement distance in the generalization process. Therefore, it can be concluded that the quality of the result is better when the spatial conflicts problem is solved using PSO algorithm.

To show the final result graphically, the original map and the displacement result map resulting from PSO and SA algorithms are presented in Figure 2a–c. Also, three different examples are selected from the dataset and the results of displacement in 10 and 20 iterations for each algorithm are shown by zooming in Figure 3. According to these examples, we can conclude that PSO algorithm performs better in reducing the spatial conflicts and displacement distance.

Table 3. 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

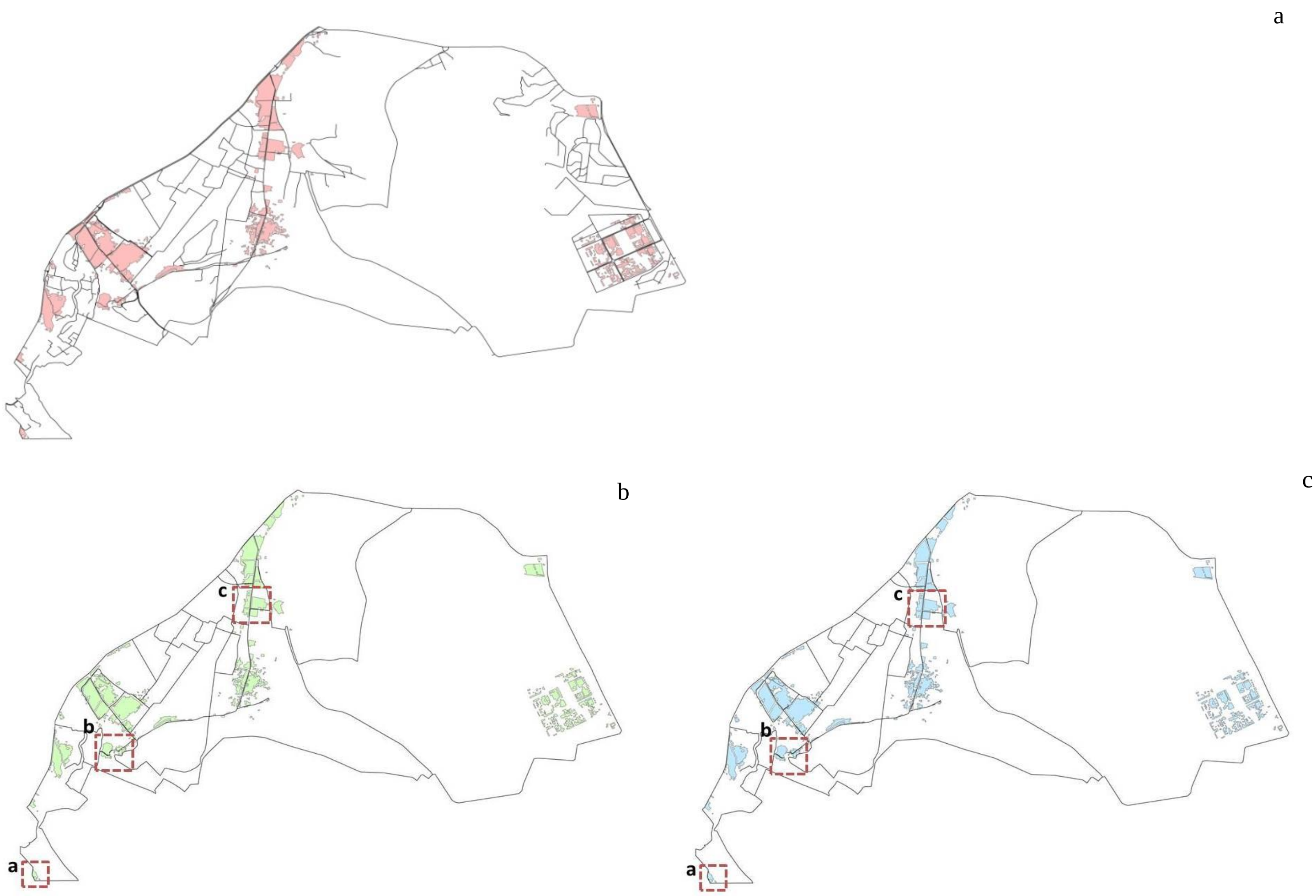

Figure 2. The 1:25k map of selected dataset (a), the generalized (1:50k) map of dataset using PSO (b), the generalized (1:50k) map of dataset using SA (c).

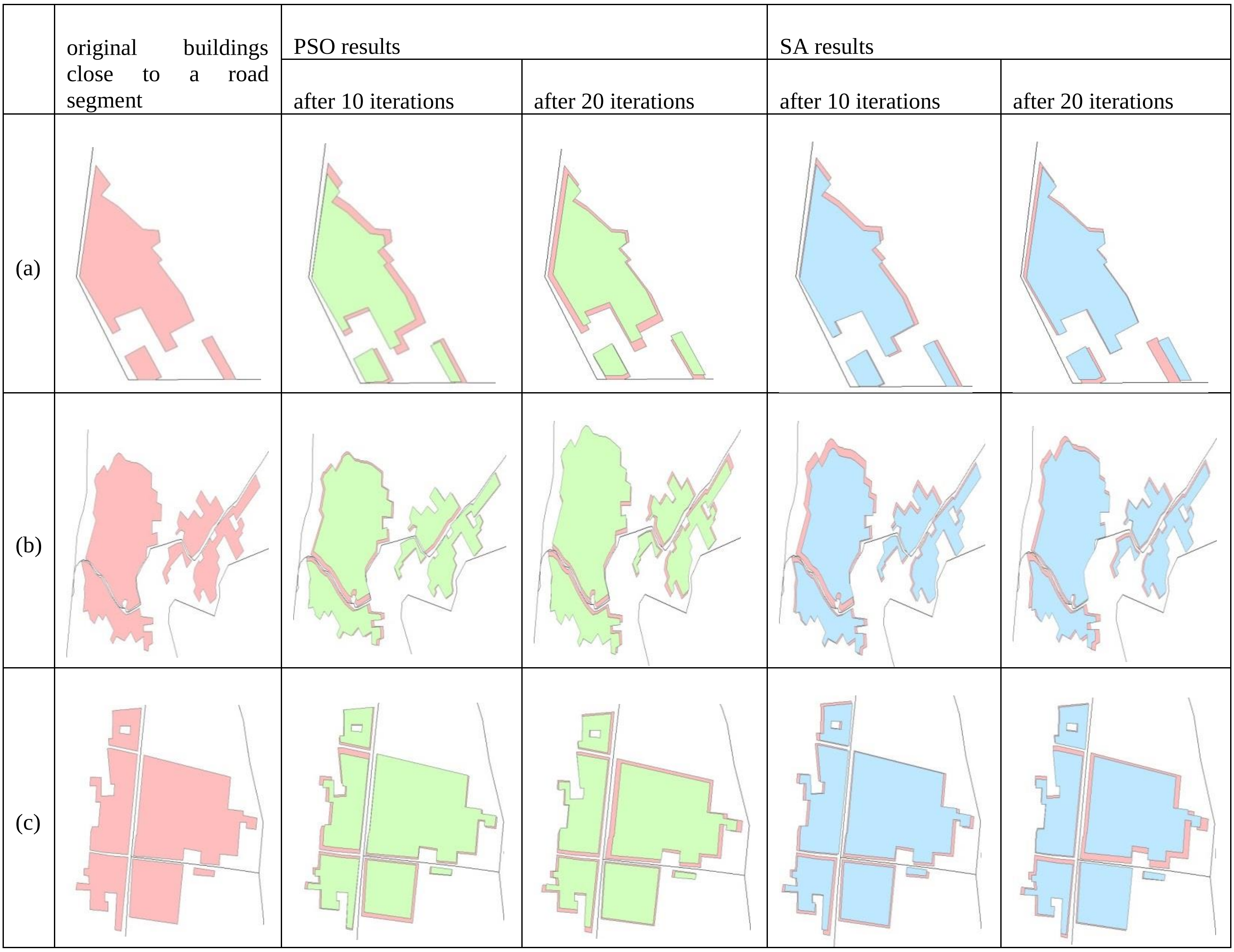

Figure 3. Three examples of conflict reduction obtained by PSO and SA algorithms for 10 and 20 iterations.

4. EVALUATION

For the purpose of evaluation, firstly we measure the harmony of the selected block before and after generalization using the ratios between the building area and the free space area, block density and the mean of the first nearest neighbor distances. In order for that, a global estimator, SumDev, is the proposed by Li et al. (2004) as follows (Equation 7):

$$\mathrm{SumDev} = \sum \mathrm{abs}(\mathrm{i} - \mathrm{j}) \tag{7}$$

Where $\mathrm{abs}(\mathrm{k})$ 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. The results are presented in Table 4. As can be seen in Table 4, the value of SumDev for both algorithms decreases when the number of iteration increases but in each corresponding iteration, it is smaller for the PSO algorithm compared to the SA algorithm. Therefore, the quality of the results is better when the spatial conflict problem is solved using PSO algorithm.

Table 4. Comparing the results of harmony assessments with the result of manual generalization.

state	No. of buildings	Total area	Ratio between the building area and the free space area (%)	Block density (%)	Mean of first nearest neighbor distance	SumDev
before generalization	478	5283921.43	5.56	5.27	46.05	-
SA after 10 iterations	279	5029572.75	5.28	5.02	47.15	1.63
SA after 15 iterations		5032417.26	5.28	5.02	46.73	1.21
SA after 20 iterations		5063761.75	5.32	5.05	46.69	1.10
PSO after 10 iterations	279	5054826.68	5.31	5.04	47.01	1.44
PSO after 15 iterations		5063901.34	5.32	5.05	46.78	1.19
PSO after 20 iterations		5091583.58	5.35	5.08	46.62	0.97

In addition to the harmony asessment, the generalized results were compared with those produced manually by cartographer. The generalized buildings are correct if they equal to the ones identified by cartographer, and denoted by tp. The generalized buildings are incorrect if they are not equal to the ones identified by cartographer, and denoted by fp. The buildings that are missed by the approach are denoted by fn. Therefore, the correctness is defined as ${}^{tp}/_{tp\,+\,fp}$ and the completeness as ${}^{tp}/_{tp\,+\,fn}$ (Du et al., 2016b; Potuckova and Hofman, 2016). The results are presented in Table 5.

The results demonstrate that the same as harmony assessment, with the increase in the number of iterations, the accuracy increases for both algorithms. But in each corresponding iteration, the correctness and completeness is higher compared for PSO compared to SA algorithm.

Table 5. 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

5. CONCLUSION

Building generalization represents an essential step in topographic map generalization. This paper presented a comparative study of two optimization approaches, i.e., PSO and SA algorithms, for the reduction of spatial conflicts in building generalization process. The objective of this study is to analyze the algorithms considering three points. One is the reduction in total conflicts; the other is the total displacement distance and the third one is their accuracy in the building generalization process. A real building dataset at 1:25k dcale is used to evaluate the algorithms in complete building generalization process. The results showed that:

1) The PSO algorithm results in fewer spatial conflicts compared to SA algorithm.

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

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

So, it can be concluded that the quality of the results is better when the spatial conflicts problem is solved using PSO algorithm. So, it is beneficial for the building generalization process.

It shold be noted that non of the algorithms could resolve all the spatial conflicts in the region. It is due to the fact that although the study area is a sparse region, in some parts of it, there is not plenty of free map space into which objects may move (e.g., example b in Figure 3). In order to solve this problem scale reduction operation is used in this study. However, it cannot of course be guaranteed to resolve all conflicts if there is insufficient map space available. So, the objective function should change in the future study for the implementation in dense areas.

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