An Evaluation and Design Support System for Urban Walkability

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Abstract

We present an operational proposal for the evaluation of walkability. Its distinguishing characteristic in conceptualising walkability is to take into account and combine three distinct elements in a multicriteria evaluation model: the availability of attractive destinations, their *effective* distances along a detailed representation of the street network *and* the *qualities* relevant to walkability of the potential paths leading to these destinations. In other words, our construction of the walkability score does not reflect only how a place is *per se* walkable, but rather what is the walkability that place is *endowed with*. We further present examples and use cases of how such an operational approach may be used (1) for the evaluation of walkability of an urban area; (2) as a "conventional" planning and decision support system, through comparing the effects of urban projects on the walkability of the area; and finally (3) as a *design* support system, with having the system itself attempt to devise possible designs and projects, given a user-defined objective to raise the walkability of an urban area.

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1. Introduction

The quality of life a place in the city is conducive to greatly depends on the places, activities and services accessible from that point in space. In such a conception of urban quality, walkability has become a pivotal, and lately much debated concept (Livi Smith and Clifton 2004, Cervero and Duncan 2003, Porta and Renne 2005, Frank *et al.* 2006, Clifton *et al.* 2007, Forsyth *et al.* 2008, Paez *et al.* 2013, Blečić *et al.* 2015). The idea of walkability is an attempt to push further and beyond the crude accessibility of places. What becomes to matter here is the *quality* of the accessibility and, to add another turn of the screw, how the urban environment (built environment, social practices, etc.) is conducive to walking: besides mere distances, it matters a great deal if a place can be reached also by foot or by bicycle, if the pedestrian route is pleasant and spatially integrated with the surroundings by good urban design, if it is brimful of urban activities, if it is well maintained and (perceived as) secure, if it is not submissive and surrendering to the car traffic whether by design or by predominant social practices of use of that space.

We have to be careful here not to underestimate the relevance of urban walkability. Afar from "just" creating cappuccino-sipping *Stadtluft*, we argue that a proper theoretical frame to locate the walkability into is the approach towards human capabilities. We use 'capability' here in the specific sense of the so called capability approach (Sen 1993): a person's capabilities are valuable states of being that a person has effective access to. Thus, a capability is the effective freedom of an individual to choose between different things to do or to be that she has reason to value. In this conception, a capability constitutively requires two preconditions: (1) the ability, the person’s internal power, detained but not necessarily exercised, to do and to be, and (2) the opportunity, the presence of external conditions which make the exercise of that power possible. A person is thus capable, has the capability to do or to be something, only if both conditions – internal and external, ability and opportunity – allow her to. The physical urban space – the city’s hardware – influence capabilities primarily through the channel of the opportunity component of capabilities.

In this contribution we present a methodology and a planning support system, *Walkability Explorer* (WE), for evaluating walkability of places. A spatial multicriteria evaluation model is used to assign walkability scores to points in urban space. We derive the scores from potential pedestrian routes along the street network, taking into account the quality of urban space on several attributes relevant for walkability. One of its notable characteristics is a certain reversal of perspective in evaluating walkability: the walkability score of a place does not reflect how that place is *per se* walkable, but instead how and where to can one walk from there, that is to say, what is the walkability the place is *endowed with*. This evaluation incorporates three intertwined elements: the number of attractive destinations reachable by foot, their walking distances, and the quality of the paths to these destinations. We show possible uses of the support system by discussing the results of a case-study assessment for the city of Alghero in Sardinia.

Furthermore, we explore the possibility of developing a *design* support tool centred on pedestrian accessibility and walkability of places. The use of the evaluation model as tools for the assessment of urban projects is straightforward: to estimate the effectiveness of a project in terms of walkability, one codifies both the current situation and the project into the system, runs the model to compute walkability scores, and then compares the results. But, what would it amount to to turn this around and address the inverse problem? Here arises an interesting prospect to have the system itself generate hypotheses of projects, given some (user-provided) objectives and constraints. There seems to reside a potential for developing not only evaluative, but also such generative procedures, in other words, to develop not only tools for assessing projects, but for designing them. In the paper we present our first take of that inverse problem, by offering a possible transposition of our approach to evaluating walkability into one such generative procedure. This, it turns out, remarkably increases operational and computational complexity. Given the in principle great amount of combinatorial options and thus a vast search space of solutions, the problem calls for specific search heuristics which proves to be an intricate challenge. There are many different routes one may try to take here. The proposal hereby presented must be seen as a preliminary exploration of one among many such possible routes. By way of example, we briefly present an application for the city of Alghero.

2. Evaluating Walkability

2.1 The Evaluation Model

The essential formal structure of the evaluation model is centred on the assumption of pedestrian behaviour as a maximisation problem (for a detailed discussion see Blečić *et al.* (2015)). A resident living at a point in urban space can walk through the street network to destinations of interest. To capture distinctions among urban opportunities, destinations may be divided into separate categories each representing a different type of urban opportunity (e.g. green areas, commercial and retail, services, etc.). We assume that a resident at a point in space will walk to available destinations a certain amount of times, and will from that derive some benefit β defined by the following constant elasticity of substitution (CES) function:

$$(\beta(x) = \left(\sum_{i=1}^{n} X_i^{\rho} \right)^{\frac{1}{\rho}} \tag{1}$$

where n is the number of available destinations, X_i is the number of times the resident visits the *i-th* destination and $1/(1-\rho)$ is the elasticity of substitution among destinations. The constraint imposed upon the pedestrian is:

$$\sum_{i=1}^{n} c_i X_i \leq M \tag{2}$$

where c_i is the cost the pedestrian foregoes to reach the destination i, and M is the available budget with a conventional constant value.

The urban street network is represented by a graph $G = (\mathcal{E}, V)$, where $\mathcal{E}$ is a set of edges and V is a set of nodes (i.e. vertices) connected by edges. A path from an origin to a destination is thus a set of interconnected edges of the graph G. Beside sole distances, we describe edges of the paths on further attributes which shape the *quality* of the pedestrian accessibility. These attributes are to represent how an urban environment is attractive for walking, characteristics such as physical features, urban design, presence (or absence) of variety of urban activities. The attributes serve to model the “cost” of a path used in the constraint expression (2).

We define the cost of a path of p edges as:

$$c = c_0 + \sum_{k=1}^{p} l_k \left(1 - \left(\sum_{l=1}^{r} w_l a_{k,l}^{r} \right)^{\frac{1}{r}} \right) \tag{3}$$

where c_0 is the fixed cost, l_k is the length of the k-th edge in the path, $a_{k,l} \in [0,1]$ is the value of that edge's l-th attribute, w_l is the weight of the attribute ($\sum w_l = 1$), and r is a parameter with $1/(1-r)$ being the elasticity of substitution among attributes. This expression yields unit variable cost of 1 when all attributes are at their lowest value (i.e. 0), and approaches 0 when attributes approach the highest value of 1.

Among many alternative paths from an origin to a destination in a street network, we plug the cheapest one into the expression (2).

The walkability score w we attribute to a point in space is the maximum benefit which, under the assumption of the behavioural model, may be yielded by a person residing at that specific point. In other words, for each node in the graph the walkability score is:

$$w = \max \beta(x) \tag{4}$$

Under the constraint given by Eq. (2), this optimization problem is solved by the following values of x_i:

$$X_i = \frac{c_i^{\frac{1}{\rho-1}} M}{\sum_{j=1}^{n} c_j^{\frac{\rho}{\rho-1}}} \tag{5}$$

As outlined above, *Walkability Explorer* (WE) assigns a walkability score to all the graph nodes, which are potential origins of trips to destinations accessible by foot. All the nodes of the graph are considered origins, while a subset of nodes closest to the centroids of attractive areas are taken as possible destinations.

To compute the walkability of an urban area, we determine the walkability score associated to each origin node and then interpolate those scores over the raster space. In particular, the walkability scores are in WE computed in the following steps:

1. using a suitable graph search procedure, the well-known Dijkstra's algorithm (Dijkstra 1959), WE determines all the cheapest paths, in the sense of Eq. (3), between all the origin nodes and all the destination nodes within a walking range of 2 km;
2. then, for each origin node, the costs of the cheapest paths to each destination node are used in order to compute the walkability score of the note, according to Eqs. (1) and (5).
3. finally, since the street network graph does not represent all the areas accessible to pedestrians, we interpolate the walkability scores assigned to nodes to a raster of a given resolution representing the urban area. Currently, to such purpose WE uses the simple Inverse Distance Weighting (IDW) method (Shepard 1968).

2.2 An Example Evaluation

To run an example evaluation, we collected the required spatial datasets for the town of Alghero in Sardinia, Italy. The baseline street network was obtained from the Open Street Map project. Additional attributes, related to the characteristics and qualities of the street edges (required to compute the costs in Eq. (3)), were obtained either through direct *in situ* observation or through inspection using Google Street View.
The edge attributes in expression (3) are intended to describe urban quality, road conditions, land-use patterns, building accessibility, degree of integration with the surroundings, safety, and other features and practices of use of space important to pedestrians. In the application, the attributes were organized into two categories: physical features and quality of urban design. In Table 1 and Table 2 we report the attributes, their weights and scales of measure used in the example evaluation. The list of edge attributes in WE is not fixed, as the software allows the user to modify and introduce further attributes, if that is required by a different descriptive and evaluative approach to walkability.

Table 1. Physical features of the path

Attributes	Weight	Scale values
Cyclability	2/30	exclusive lane (0.8); off road lane (0.5); on road lane (0.3); prohibition (0.1)
Width of the roadway	1/30	pedestrian way (0.8); one lane street (0.6); two lane street (0.5); three lane street (0.3); four lane street (0.1)
Car speed limit	2/30	pedestrian way (0.8); 20 Km/h (0.7); 30 Km/h (0.5); 50Km/h (0.3); 70 Km/h (0.1)
One way street	1/30	pedestrian way (0.8); yes (0.5); no (0.1)
On-street parking	1/30	prohibited parking (0.8); permitted (0.5); illegal parking (0.1)
Width of (walkable) sidewalk	2/30	wide (0.8); comfortable (0.7); minimum (0.5); inadequate (0.3); lacking (0.1)
Separation of pedestrian route from car roadway	2/30	marked-strong (0.8); weak (0.5); lacking (0.1)
Path slope	2/30	smooth (0.8); light (0.5); rise (0.1)
Paving (quality and degree of maintenance)	2/30	fine (0.8); cheap (0.5); bumpy (0.1)

Table 2. Quality of urban design features

Attributes	Weight	Scale values
Public illumination	1/16	Excellent (0.8); good (0.6); inadequate (0.3); lacking (0.1)
Shelters	1/16	Strong (0.8); weak (0.5); lacking (0.1)
Sedibility	1/16	Extended (0.8); thin (0.5); lacking (0.1)
Services and activities	1/16	Continuous (0.8); on the average (0.6); thin (0.3); lacking (0.1)
Attractiveness from an architectural and urban viewpoint	1/16	preponderance of pleasant elements (0.8); presence of a few pleasant elements (0.6); lack of pleasant or disturbance elements (0.4); presence of a few disturbance elements (0.2); preponderance of disturbance elements (0.1)
Attractiveness from an environmental point of view	1/16	preponderance of pleasant elements (0.8); presence of a few pleasant elements (0.6); lack of pleasant or disturbance elements (0.4); presence of a few disturbance elements (0.2); preponderance of disturbance elements (0.1)
"Softness" – "permeability" of the public-private space	1/16	Permeable (0.8); filtered (0.5); separated (0.1)
Urban texture	1/16	Dense (0.8); park or green space (0.6); low density; green open spaces

The attractive nodes were divided into three categories: commercial/retail (including supermarkets, markets and food stores, bakeries, butcher shops, fish shops and tobacco shops), services (health services, schools, banks and public offices) and recreational areas (urban parks, sport facilities, beaches). These data were harvested from freely available data sources: the Bing Maps and the Yellow Pages website.
In Fig. 1. we report the computed costs of the street edges and the localisation of attractions used in the evaluation, divided by category.

Given the location of attractions in space, WE identifies the areas of attraction using a regular grid of cells, according to a resolution set by the user, and constructs the set of destination nodes (i.e. the destinations are rasterized). It is worth noting that the size of raster cells can be set independently for different types of attractions. Then, for each attractive cell, the software builds the set of destination nodes by finding the node of the street network closest to the cell's centroid.
Finally, by running the computation following the described procedure, the walkability scores are determined. To shorten the run time, WE implements a parallel multi-thread computation to exploits the available multi-core-CPU computers.

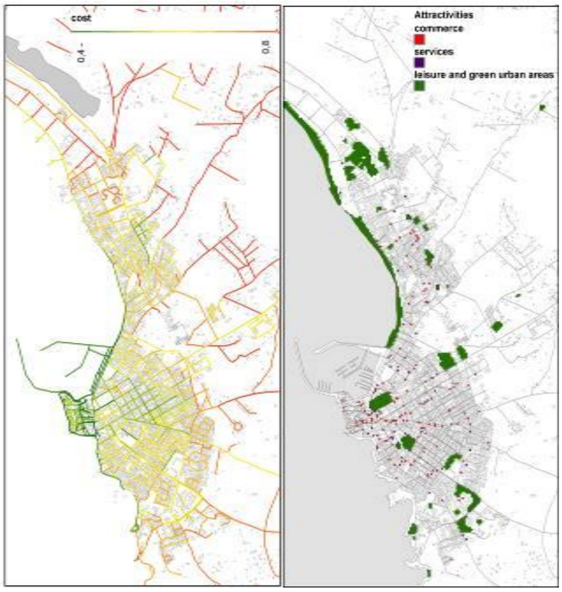


Figure 1. Computed "costs" of street edges (left) and map of destinations (right).

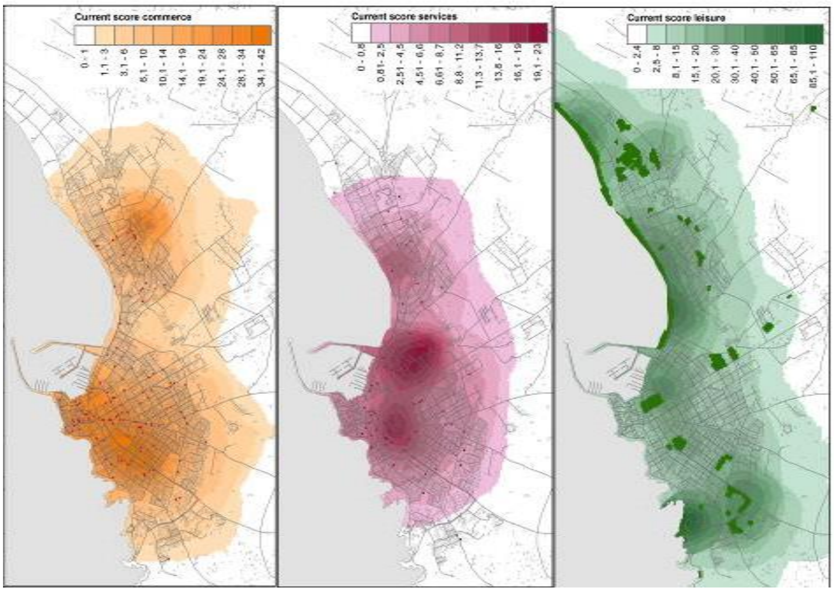


Figure 2. Walkability scores for the central area of the city of Alghero, divided by category.

The final output are geo-referenced walkability scores related to each of the categories of destinations. Fig. 2 shows the walkability scores for the central area of the city of Alghero, divided by category.

All the output datasets can be exported in a suitable GIS format, and the raw data can be saved as CSV files for further analysis.

It is important to note that, as a way of planning and decision support, WE may be used both for the assessment of the current walkability as well as for comparing it to a design/project that needs to be evaluated in terms of walkability. In this case the user needs to input both the current scenario and the one derived from the project (shape and characteristics of the street networks, land-uses, etc.). Then, besides computing walkability scores of the two scenarios, WE is capable of generating the maps of variation of walkability scores between the current and the alternative scenario, and, again, allows these data to be exported in a GIS and CSV format.

3. The Inverse Problem: From Evaluation to Design

3.1 The Optimization

We now turn to a possible take of the inverse problem, that is to say, given the above specified evaluation model of walkability, how to have the system itself generate design proposals with a set of actions (improvements of the street network) that would improve the walkability of a specific urban area.

According to the evaluation model defined above, such a design can be formalized as:

$$P = \left\{ \left\langle e_1, \Delta\eta_1 \right\rangle, \ldots, \left\langle e_q, \Delta\eta_q \right\rangle \right\} \tag{6}$$

where e_k denotes an edge of the street network and $\Delta\eta_k \in \left]-1,0\right[$ is the corresponding reduction of its cost factor η_k. It is worth recalling that, in general, a reduction of the cost factor ($\Delta\eta_k$) can be obtained by improving somehow the attributes $a_k = \left\{ a_{k,1}, \ldots, a_{k,n_a} \right\}$ of the edge e_k (see Eq. (3)).

We evaluate the effectiveness of a design *P* with respect to a subset $\bar{S}$ of origin nodes, which are representative of the urban area whose walkability must be improved. Given the set of destination nodes *D*, first we modify the graph representing the street network to account for all the $\Delta\eta_k$ included in *P*; then we use the procedure described above to compute the walkability score w_i for each node $n_i \in \bar{S}$. Subsequently, we define the walkability score $Walkability(\bar{S} \mid P)$ of $\bar{S}$ as the average value of all w_i.

Moreover, we assume that, for each e_k, there exists a function $Effort_k$ that provides the minimum effort (e.g. in terms of money, time, etc.) required to achieve a given decrease $\Delta\eta_k$ of the cost factor. Such a function may simply be estimated by experts, on the basis of the condition of the street, which is represented by its current vector of attributes. Alternatively, it can be pre-computed using the optimization procedure and by attributing an effort to each variation of the attributes. We define the effort *Effort*(*P*) of a design *P* as the sum of all the efforts required by its edges.

A typical design problem consists of devising a set *P* which maximizes the benefit $Walkability(\bar{S} \mid P)$ with the minimum *Effort*(*P*). This could be in principle we accomplished through a trial-and-error procedure in which the user "manually" modifies edge attributes and then runs WE to compute how such changes affect the walkability in the area of interest. However, the search space (i.e. the set of all possible designs) is typically huge. Also, the effects of edge changes on a complex graph are not always straightforwardly intuitive and some suitable solutions may be non-trivial. For these reasons, such a procedure would hardly result in efficient and satisfactory design solutions.

In this paper, we propose an automatic procedure to support devising a design of walkability improvements. We formulate the design problem as the following bi-objective constrained optimization problem:

$$\begin{cases} \max\limits_{\mathcal{P} \subset \Pi} \; Walkability(\bar{S} \mid \mathcal{P}) \\ \min\limits_{\mathcal{P} \subset \Pi} \; Effort(\mathcal{P}) \\ \bar{\eta}_k < \eta_k + \Delta\eta_k < 1 \quad \forall \, \langle e_k, \Delta\eta_k \rangle \in \mathcal{P} \end{cases} \tag{7}$$

where $\bar{\eta}_k$ indicates the minimum achievable value for the cost factor of e_k. Such minimum values should be estimated on the basis of the physical conditions of the streets.

An approach to address this optimization problem may consist in its transformation into a single-objective one by combining the two functions *Walkability* and *Effort*, with some parameters (i.e. weights) grounded on the decision maker's preferences. A major issue with such an approach is that it requires an explicit statement of preferences over the two objectives by the decision makers prior to the solution process, which must be repeated if the preferences change.

For the above reasons, the approach adopted in this study consists of maintaining the two separate objectives and generating a set of solutions to be presented to the decision maker for consideration. With this approach we construct a set of non-dominated solutions using a suitable metaheuristic. Then, the solution eventually chosen by the decision maker is obtained by examining and exploring the various trade-offs between the achieved walkability improvement and the corresponding effort in the set of non-dominated solutions.

In the current version of WE, the metaheuristic adopted for solving the above problem is a multi-objective Genetic Algorithm GA (Fonseca and Fleming 1995, Coello *et al.* 2002). In particular, we have use the NSGA-II (Deb *et al.* 2002), which has been extensively investigated and successfully tested (Deb *et. al.* 2002, Jensen 2003, Nojima *et al.* 2005, Drzadzewski and Wineberg 2005, Blečić *et al.* 2007).

Following the NSGA-II algorithm, we create a number of frontiers of non-dominated solutions using Goldberg's "non-dominated sorting" procedure (Goldberg 1998).

When each frontier has been created, the so-called "crowding distances" (i.e. normalized distance to closest neighbours in the frontier in objective space) are assigned to its members, to be used in the next phase with the purpose of promoting a uniform sampling of the Pareto set.

The initial population is composed of n_p random individuals, each with a different number of edges within a prefixed maximum: each edge of a candidate solution is randomly drawn from a suitable set $\varepsilon^* \subset \varepsilon$. Ideally, in order to speed up the convergence process, ε^* should not include streets with very low probability of affecting the walkability to maximise. In the current implementation, we construct ε^* as follows: first we include all the cheapest paths between each couple of nodes $n_i \in \bar{S}$ and $d_j \in D$; then, we make a first order expansion of ε^* by including all the edges linked to the edges already in ε^*. The improvement of the cost factor $\Delta\eta$ for each edge is chosen randomly in the initial population, in accordance with the bound constraint in Eq. (7). Thus, the optimization process evolves that initial population to obtain a suitable set of non-dominated designs.

The relevant aspects of the heuristics are the recombination and the mutation operators. At each generation, n_p selected individuals are recombined for producing n_p offspring individuals. Selection is performed by binary tournaments (Deb *et al.* 2002): between two randomly drawn individuals the one with the lowest frontier number wins. If the individuals come from the same frontier, the one with the highest crowding distance wins, since a high distance to the closest neighbours indicates that the individual is located in a sparsely populated part of the frontier. The recombination operator, which is applied with probability ε_c, is defined as follows: first we decode the two selected parents p_i and p_j into the two candidate solutions P_i and P_j, respectively; then we compute the set $\overline{P} = P_i \cup P_j$; next, we randomly split the set $\overline{P}$ into two new candidate solutions P_i^* and P_j^*; finally, the latter individuals are encoded and stored into the offspring population.

As for the mutation operators, applied to each offspring after the recombination, these are:

- *edge removal*: each edge of the individual (a design) can be removed with some probability ε_r;
- *edge insertion*: an edge can be added to the individual with some probability ε_a (to promote a gradual exploration of the graph, the additional street edge is randomly chosen between the edges to an edge which is already included in the offspring design being examined;
- *random variation of cost factor reduction*: for each element $\langle e, \Delta\eta \rangle$ of the offspring, the value of $\Delta\eta$ is randomly changed, in accordance with the bound constraint, with some probability ε_v;

The algorithm is elitist, in the sense that out of the $2n_p$ (i.e. parents plus offspring), the best n_p individuals are kept for the next generation.

To evaluate the new individuals at each generations, we use an incremental update of the data structure obtained during the preliminary walkability assessment. To this purpose, we adopted the algorithm proposed by Ramalingam and Reps (1996) which allows to avoid repeating a complete Dijkstra's search for each node in $\overline{S}$.

3.2 Generating Designs: An Example

By way of example, the above approach was applied to the Alghero dataset. The effort corresponding to the improvement of a street edge was computed as $Effort_k = -l_k \Delta\eta_k$. The minimum achievable value for the cost factor $\overline{\eta}$ was set to the value of 0.2 for all edges. The population of n_p=100 individuals was evolved trough 500 generations of the NSGA-II algorithm with the parameters ε_v=1.0, ε_r=0.15, ε_a=0.1 and ε_v=0.2.

The key results are presented in Fig. 3. The graph to the right shows the calculated Pareto set of design solutions: each project is plotted against its walkability score and the related effort necessary for the implementation of the design. To the left we show what one such solution (the one highlighted in green) entails. Here, one may observe which nodes were used as destinations and all the edges contemplated by the project to be improved to obtain the established increase of the walkability scores.

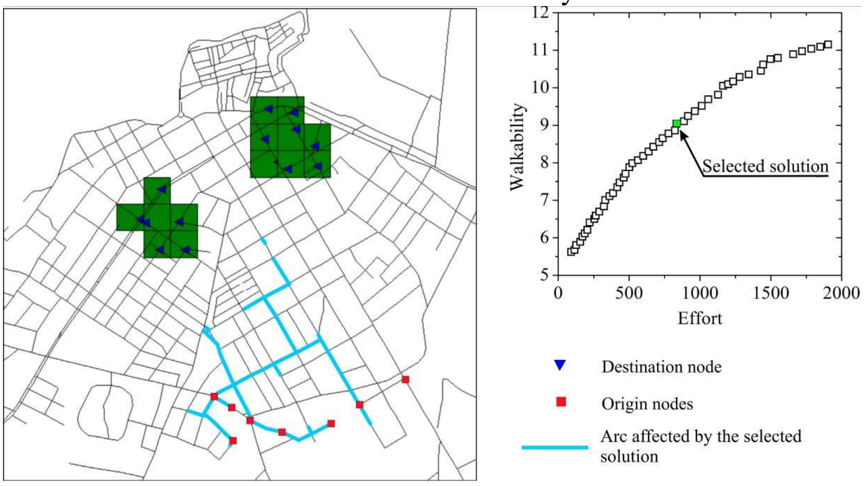
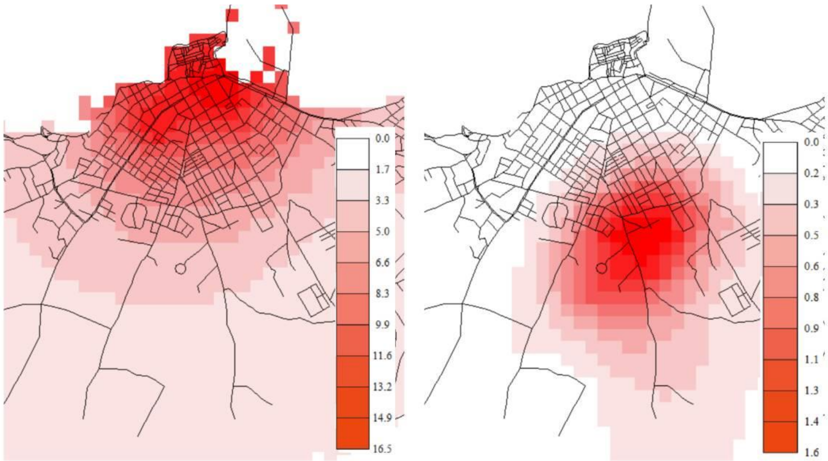


Figure 3. The set of solutions (graph to the right). The map to the left shows the details of the selected solutions: the destination nodes, the user chosen origin nodes whose walkability to improve, and street edges involved in the solution.



Current score Score variation

Figure 4. Interpolated maps of the current walkability score and its variation due to the design solution highlighted in Fig. 3.

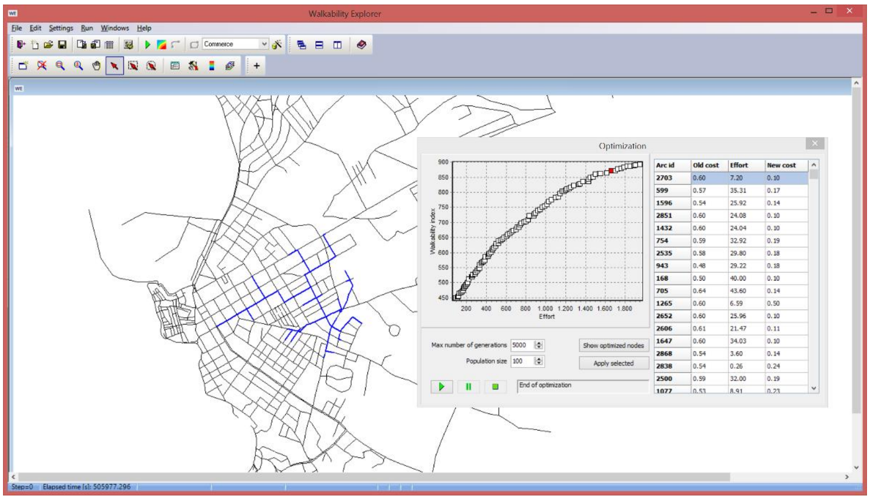


Figure 5. Exploration of design solutions in *Walkability Explorer*.

The spatial distribution of the variation in walkability scores due to the project is represented in Fig. 4. This map provides thus (on a wider scale) the effect of the project on the overall walkability of the urban area. The software allows (Fig. 5.) to further examine the solutions more in detail by drilling down into the proposed changes for each edge of the graph.

4. Conclusions and Prospects

The distinguishing feature of our operational conceptualization of walkability is to take into account three distinct elements: (1) the availability of attractive destinations, (2) their *effective* distances along a detailed representation of the street network, and (3) the *qualities* relevant to walkability of the paths leading to these destinations. In other words, our construction of the walkability score does not reflect only how a place is *per se* walkable, but rather what is the walkability the place is *endowed with*.

We further presented how such an operational approach may be used (1) for assessing the walkability of an urban area; (2) as a "conventional" planning and decision support system, through comparing the effects of urban projects on the walkability of the area; and finally (3) as a design support with the system itself devising possible designs and projects, given a user-defined objective to raise the walkability of an urban area.

There are several potentially promising lines for future research. One, quite practical, is to better integrate data sources and further automatize the harvesting of the available datasets. One the methodological side, the approach opens the possibility to incorporate differential evaluation of walkability for different populations and profiles of pedestrians based on age, gender, disabilities, and other social variables.

Finally, there seems to exist a promising perspective for tools for assisting urban design processes through a tight human-computer interaction. It is important to note that in the case of walkability this goes beyond the problems of a standard road network optimization since, as we have seen, it involves much "thicker" multidimensional description of the urban environment; and such multidimensionality significantly rises the bar of computational complexity. Although we have shown a possible route of reduction of the problem to make it computationally more tractable, further investigation is necessary to more systematically explore if and what other approaches and search heuristics may perhaps prove to be better suited for the task. Given the potential service such tools may offer for the future urban design and planning, it seems to us a research line worth pursuing.

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