Not Arbitrary, Systematic! Average-Based Route Selection for Navigation Experiments

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Abstract

While studies on human wayfinding have seen increasing interest, the criteria for the choice of the routes used in these studies have usually not received particular attention. This paper presents a methodological framework which aims at filling this gap. Based on a thorough literature review on route choice criteria, we present an approach that supports wayfinding researchers in finding a route whose characteristics are as similar as possible to the population of all considered routes with a predefined length in a particular area. We provide evidence for the viability of our approach by means of both, synthetic and real-world data. The proposed method allows wayfinding researchers to justify their route choice decisions, and it enhances replicability of studies on human wayfinding. Furthermore, it allows to find similar routes in different geographical areas.

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1 Introduction

Selecting a route for a human wayfinding study in a systematic manner is a non-trivial task. Despite its potential impact on the results, reasonable justifications for routes based on their features are often neglected. In this paper, we propose, implement and evaluate a methodological framework which enables researchers to choose a route for human wayfinding experiments in a given area according to predefined, weighted criteria. The determined routes are – with respect to these criteria – representative for a (weighted) average route for the chosen area. Using this framework will, therefore, lead, among others, to an increased comparability and replicability of in-situ wayfinding studies.

Starting with the replication crisis in psychology [34], reproducibility and replicability have both seen increased interest in all subfields of geographical sciences in recent years (see e.g., [32, 35, 20, 24]). At the same time, studies which aim to understand human wayfinding and/or how interactive assistance can be provided to wayfinders have gained momentum [21, 12]. These research efforts will likely be continued in the future, as there is neither a

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general agreement on algorithms nor route descriptions or an anywhere close to definite understanding of the interplay between spatial cognition and the assistance provided by mobile navigation companions. While there has been some recent progress in terms of reproducibility (i.e., software and data are made available to the scientific community and rerunning the analysis using the software and data yields the published results, see [6]), e.g., through initiatives like the AGILE initiative on reproducible publications (see also [32]), increasing the level of replicability may be much harder to achieve. In particular, up until now, the replicability of wayfinding studies often suffers from the possibility to choose a route in a systematic manner: the decisions which led to the choice of a particular route are often not made explicit, leading to the impression that routes are often chosen in an ad-hoc manner (see Section 2). As a result, oftentimes information other than length, number of decision points, and a rough classification of the urban environment (e.g., European) is not given. As a consequence, the impact of differences in route properties cannot be assessed in an appropriate manner if researchers fail to replicate the results.

2 Related Work

This section provides a thorough overview of route features in studies involving wayfinding tasks. It provides the basis for the set of features, we use in our methodological framework. (see Section 3). In order to gain an insight into common practice among researchers to justify their route choices and the route characteristics they pay attention to, we have systematically screened six major venues (conferences and journals) in the broader area of geographic information science and related fields since 2010.

While our search is not exhaustive by any means, the number of papers screened is still suitable to provide a reasonably grounded insight into the state-of-the-art. In identifying relevant papers, we focused exclusively on studies involving either wayfinding tasks by participants or studies, in which routes were presented to users, e.g., on maps. This implies, that we deliberately excluded all studies involving route retrieval from memory without performing an actual wayfinding task or which involved human wayfinding without predefined routes.

Overall, 32 papers were found which present studies on wayfinding/navigation in both, virtual and real-world environments. Each of the relevant articles/papers found was checked for the rationale researchers have given for the chosen route and which route characteristics they have mentioned explicitly.

Table 1 reveals several important insights regarding common practices among researchers: The three most often named aspects are: the length of a route (mentioned by 16 publications), the type (e.g., a residential area) of environment a study was conducted in (15), and the name of the city/town of a study (11). While these criteria are the most frequent ones, it is important to note that only half of the papers mention route length and type of environment whereas the name of the city/town is stated only by one third of the papers explicitly. In addition to basic route data and information about the local environment of different granularity, a variety of features mentioned by researchers deal with decision points (DPs). We consider each intersection on a route as a decision point, which is neither the start nor the end point of the route. While authors describe at least the overall number of DPs and the proportion of those DPs which require a turn, the layout of the DPs is given rather rarely. Several other aspects related to route instructions, visibility of environmental cues and – in case two or more routes are compared – how routes relate to one another are mentioned occasionally.

Table 1 Overview of route features named (multiple features per paper possible) in human wayfinding studies in major research outlets since 2010. Relevant papers for the AGILE conference: [1, 14, 23]; for the GIScience conference: [38, 29, 19]; for the COSIT conference: [40, 46, 47, 18, 22, 11, 3, 2]; for the IJGIS: [26]; for the LBS Journal: [13, 37, 39]) and for the SCC Journal: [33, 45, 49, 27, 36, 17, 43, 25, 48, 42, 16, 7, 31, 44].

	Feature	AGILE	COSIT	GIScience	IJGIS	LBS	SCC	Freq (N=32)
Basic Route Data	length	3	4	1	1	2	5	16
	walking duration	0	2	2	0	0	0	4
	name of city	1	4	0	0	2	4	11
	size of area	0	0	0	0	0	1	1
Local Environment	uniformity of env.	0	1	0	0	0	0	1
	type of env. (e.g., residential)	1	2	1	0	2	9	15
	terrain (e.g., flat)	0	1	0	0	0	0	1
	complexity of env. (e.g., narrow streets)	0	4	0	0	1	3	8
	type of walkways (e.g., sidewalk)	0	0	1	0	1	0	2
Decision Point / Intersection	#DP	1	1	1	0	0	3	6
	#DP with turn	2	1	0	0	2	3	8
	#type of turn (l,r, non-turn)	1	0	0	1	0	0	2
	Inclusion of diff. actions at DP	1	0	1	0	0	0	2
	DP layout (e.g., 3-way, 4-way) described	1	1	0	0	0	1	3
	variety of DP layouts mentioned	0	0	2	0	2	0	4
	DP density	0	0	0	0	1	0	1
	Distance between DP	0	1	0	0	0	0	1
Route Instruction Features	inclusion of landmarks	0	0	1	0	1	4	6
	inclusion of street names	0	0	1	0	0	0	1
	Destination (landmark)	1	0	0	0	0	0	1
View / Visibility related	views offered (e.g., open vista)	0	0	1	0	0	0	1
	visibility of dest. from start (or vice versa)	0	1	0	0	0	1	2
	long-distance vistas	0	1	0	0	0	1	2
	visibility of street names	0	0	0	0	0	1	1
Relation to other Routes	equal length	0	0	0	0	0	1	1
	equal starting and end points	0	0	0	0	0	1	1
Number of distinct criteria		9	13	10	2	9	14	26

Taken together, this overview of common practices provides evidence for a lack of proper justification of route choices and only very basic features of routes being made explicit. In particular, half of the publications do not even mention basic properties, such as route length, and even environmental and decision point-related aspects are insufficiently described. This is, from our perspective, a clear barrier to any attempts to the replicability of these research results.

3 Route Selection Criteria

It is obvious that route selection is deeply intertwined with a study's research question. The literature review above has revealed, however, that this selection is often insufficiently justified. Moreover, even basic route properties are often not made explicit. This may be a hint to the practice to use ad-hoc choices for routes, a decision which may result in a considerable bias stemming from route choice. Even for those studies, which want to assess the impact of a given route, it would be desirable to be able to quantify the degree as to which a chosen route represents a special case given a set of criteria researchers want to take into account. The possibility to select routes for human wayfinding studies in a systematic and reproducible manner is, therefore, highly desirable. In order to achieve scientifically valid results, researchers interested in conducting (not only replicating) human wayfinding studies must base their research on a route, which is selected in a systematic and reproducible manner. For many of these studies, it is desirable not to use a route which would represent a special case given the researcher's requirements about routes. In human wayfinding studies in real-world, the population of routes to select from encompasses millions of possible routes of a given number of decision points for any area of non-trivial size. Given these figures, selecting a route based on the average of all routes fulfilling the researchers' requirements seems reasonable for those studies which do not use a route as an independent variable. Outliers are expected to have only a small effect as the population is vast, and the number of criteria to be taken into account is large. Therefore, the best possible route to be chosen would be a route, which meets the average for all criteria a researcher wants to take into account as close as possible. We refer to such a route using the expression *average route* because it is average-based. As mentioned above, even those studies in which route is an independent variable, knowing the deviation from the average route in an area may provide researchers with valuable information to interpret their results.

In order to make research more comparable and to provide other stakeholders (scientists, urban planners, politicians etc.) with assistance to choose one route for their needs, we present an approach which finds a route which is as close as possible to a theoretically existing average route in a given area. The idea is that a route selected in such a systematic manner should provide more transferable results as it reflects the characteristics of the specified area.

Based on the set of criteria currently used by researchers (see Section 2) our framework takes the following criteria into account. We base the decision made for in-/exclusion on both, prior research practice and the widespread availability of data:

Pre-emptive criteria

Researchers must select, first and foremost, an area in which they want to conduct their study in. In accordance with the widespread report of this criterion, we use the number of decision points (DPs) as a criterion researchers must specify. If researchers wish to do so, they can additionally provide a minimum and maximum route length.

Used criteria

According to the literature reviewed, researchers consider criteria related to DPs as important. Therefore, our framework considers the *average number of options a DP* offers and the *number of n-way intersections* on a route – both of which are derived from the intersection framework [10]. The same framework [10] provides information about the *regularity of a DP* (the sum of angles branches need to be rotated in order to create a regular intersection, see [10, p. 3:4] for further details). As a fourth DP-related aspect, we consider the *number of right, left and non-turns* at DPs on a route. We calculate these properties according to the point orientation algorithm [4]. In order to count non-turns and avoid false negatives we use a 10 degree threshold, i.e., a 20 degree cone, to identify continuations. Undoubtedly, landmarks play an important role in human navigation. However, we lack sources of salience values for arbitrary regions. Consequently, we use points of interest (POI) as a proxy (see e.g., [9] or [41] for publications with a similar approach). As there is no commonly agreed definition of POI available, we extract POIs from OpenStreetMap data based on tag `amenity=*`. Our methodological framework, however, is open to other definitions researchers may want to employ. We take two POI-related criteria into account: *the average number of POIs at a DP* and the *uniqueness of a POI category at a DP*. The average number of POIs on a route is given by the amount of POIs within a given radius from any DP divided by the number of DPs. The uniqueness of a POI, according to Rousell and Zipf [41], is defined as $\frac{1}{j}$ where j is the number of POIs of the same type (e.g. restaurant) in the considered set. Finally, two environmental features are considered: *Slope* (shares of route with negative, positive and zero slope sourced from a digital elevation model[1]) is taken into account as a proxy for criterion terrain, whereas land cover data (Urban Atlas[2]) reflect the *type of environment*.

[1] `https://www.wien.gv.at/ma41datenviewer/public/`, last access June 5th, 2020
[2] `https://land.copernicus.eu/local/urban-atlas/urban-atlas-2012`, last access March 20th, 2020

This list can be extended if more data is available or of particular interest for a navigation study to be conducted. In short, we are aiming to get as close as possible to the average route based on user-defined weights for route features in a given area.

4 Methodology

Given a certain area in a built environment, we aim at ranking all possible routes with a given number of DPs. This ranking is based on the average of all routes in this area according to a set of given criteria (see Section 3). The closer a route is to the average values, the higher this route will be ranked. In the following we provide a step-by-step description of the required computation steps. At the end of this section information about software and hardware used is provided. Our street network data are based on OpenStreetMap. The computations are based on a graph created out of nodes representing intersections and edges representing the street segments. For a detailed description of all data sources see Section 3.

Step 1: Extracting all potential routes. We represent *all* potential routes[3] in the given area with their criteria as a decision matrix $\boldsymbol{X'}$. As these criteria are measured on different scales, a z-score standardization is applied in order to normalize the values, i.e., a z-score of $z = 0$ represents the average. Since we are interested only in the deviation from the average, $\boldsymbol{X'}$ contains only absolute values of z-scores.

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \dots & x'_{1m} \\ x'_{21} & x'_{22} & \dots & x'_{2m} \\ \dots & \dots & \dots & \dots \\ x'_{n1} & x'_{n2} & \dots & x'_{nm} \end{bmatrix} \tag{1}$$

where n denotes the number of routes and m the number of criteria. In order to retrieve all possible routes of a certain number of DPs without loops, a street network graph was utilized. This can be approached as a subgraph isomorphism problem, which is NP-Complete. Although street networks can be modeled as planar graphs (for simplification reasons) in reality they are not [5]. Thus, the subgraph isomorphism problem on non planar graphs grows in general, exponentially. However, there are algorithms with acceptable practical execution time[8].

Step 2: Best possible solution. Based on the z-scores for all criteria, we retrieve the *best possible solution* A^+ (see Eq. 2): This is an artificial (and unlikely to exist) route which comprises the minima of all z-scores, i.e., it is as close to the average of all criteria one can get.

$$A^+ = (y_1^+, y_2^+, \dots, y_m^+) \qquad where \quad y_j^+ = \min_{i=1,2,\dots,n} x'_{ij} \tag{2}$$

The best possible solution contains the minimum for each criterion. A value of 0 means that this value reflects the global mean perfectly. Negative values are not possible due to the performed standardization step.

[3] It is important to note that users of the proposed method are free to take any type of routes into account,i.e. routes w/o loops, shortest path between two distinct points, round tours etc.

Step 3: Weighted similarity. There are several spatial as well as spatio-temporal similarity measures available for a variety of problems [15, 30]. We identified the cosine similarity and the weighted euclidean distance as the most promising ones for our approach. The cosine similarity measure, which is widely used for multidimensional data, had to be discarded after encountering counter-intuitive results during testing. The explanation for this discrepancy between intuition and hard numbers is that cosine similarity measures only the angle between two normalized vectors, and therefore ignores the magnitude of difference between them.

As described earlier (see Section 3), researchers can specify weights for each criterion according to their research interest (i.e., the higher a weight, the more important an average value of a characteristic is to a researcher). These weights are used during the distance calculation between a route and the best possible solution. Each route is compared to the best possible solution (equation 2) by means of the n-dimensional weighted euclidean distance: In Equation 3, x'_j represents the j-th criterion of a route and w_j is the weight for this high-level criterion.

$$dist = \sqrt{\sum_{j=1}^{m} w_j (x'_j - y_j^+)^2} \tag{3}$$

A high-level criterion is, for example, the regularity of a decision point which can be represented by the sum of angles needed to obtain a regular intersection [10]. It is, however, not reasonable to build averages across different n-way intersections. Therefore, the sum of angles is computed for each n-way intersection (called subdimension) separately. For example: If seven is the largest number of branches for all intersections in the area-of-interest, the sum of angles is calculated for 3- to 7-way intersections separately. In this particular example each subdimension would have a weight of $w_j/5$, where w_j is the weight assigned to criterion *decision point regularity*. The sum of the weight vector is 1.

Step 4: Ranking of results. Finally, all routes are ranked according to their distance (equation 3) to the best possible solution (equation 2). The smaller the distance, the closer a route is to the average in the area of interest, given the user defined weights for the applied criteria.

Implementation. This paragraph specifies the software and hardware used to implement our approach. In order to find all possible routes without loops (step 1) SageMath 9.0 with its SubgraphSearch function[4] was used, whereas steps 2-4 were implemented in Python 3.6. Two features from the real world example (see section 5.2), namely, the *average number of POIs per DP* and *type of environment* were calculated in a PostGIS (v 2.4) database. All analyses run on an AMD Ryzen Threadripper 1950X 16-Core Processor, 3400 Mhz, with 64 GB RAM.

5 Evaluation

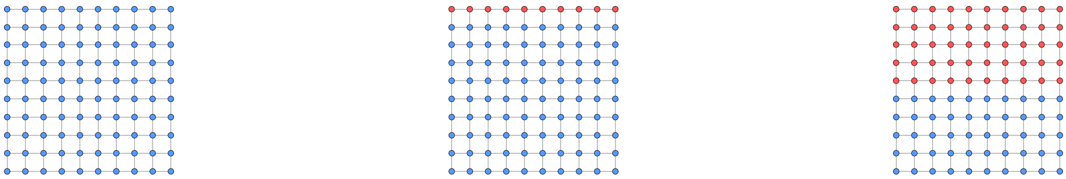
As a proof of concept, we first evaluate our approach on synthetic data (subsection 5.1). Using synthetic data enables us to use predefined values for all criteria and, thereby, formulate the expected results. We then continue with a real-world example in Vienna, Austria (see subsection 5.2).

[4] `http://sage-doc.sis.uta.fi/reference/graphs/sage/graphs/generic_graph_pyx.html#sage.graphs.generic_graph_pyx.SubgraphSearch`, last access June 5th, 2020

5.1 Synthetic data

We use 100 x 100 regular grid graphs as synthetic data. The graph used has 10 000 nodes and 19 800 edges. All edges have the same length and characteristics (which is a difference to the real-world data, see Section 5.2). We distinguish between type I and type II nodes. While type I nodes have 3 POIs all of which have unique categories, type II nodes have 6 POIs which show an average uniqueness of their categories of 1/3. Therefore, routes will have different average POI numbers due to different proportions of type I and II nodes in a route. They have different characteristics regarding POIs in order to be able to observe changes in results. It is important to note that the order of magnitude of these differences does not matter as long as it is unequal to 0. The 4 corners of the grid have only 2 edges and are considered as "2-way intersections": Taking them into account is reasonable to show that our approach takes the global distribution (frequency) of n-way intersections into account. All nodes along the border of the graph, with exception of the 4 corners points just mentioned, have 3 edges. All other nodes have 4 edges, i.e., they are regular 4-way intersections.

For all evaluations on synthetic data we set the number of decision points to $k = 7$. This number was chosen due to computation time limitations, which is reasonable based on the fact that the route recommendation algorithm is NP-Complete (due to the subgraph search problem). Based on all these routes the best possible route was calculated (see equation 2) as target route. In total, 55 396 400 possible routes without loops (represented as subgraphs) having 7 DPs plus 1 starting and 1 end point were found in this synthetic graph. These routes do not have to be a shortest path between two points. Routes have, in general, the same characteristics (e.g., slope) but they vary considering with respect to the type of actions taken at decision points (i.e., turning right or left and continuations).



(a) **(b)** **(c)**

Figure 1 Schematic Representation of Synthetic Data (data used were 10 times bigger, but with the same ratios of type I (blue) and type II (red) nodes): (a) Scenario 1: Regular grid network with only nodes of type I; (b) Scenario 2: Regular grid network with ratio 9:1 of type I to type II nodes; (c) Scenario 3: Regular grid network with equal shares of type I to type II nodes.

We evaluate our approach with respect to synthetic data based on three scenarios, which differ in the proportion of type I and II nodes (see Figure 1). Each of the scenarios share three high-level criteria, namely the number of 2-, 3-, 4-way intersections, the sum of angles needed to obtain regular 3- and 4-way intersections [10] and the frequency of right and left turns and non-turns at decision points.

Scenario 1

In this scenario the whole 100 x 100 regular grid network consists of type I nodes, only (see Figure 1a). 97% of all possible routes contain 4-way intersections only and all of these are regular 4-way intersections. The average number of right-, left- and non-turns is 2.18, 2.18 and 2.64, respectively. Based on these figures we expect the route with the least distance to the average route to have 4-way intersections only, 2 right, 2 left and 3 non-turns at DPs. As all intersections are regular, the sum of angles equals zero and, therefore, is omitted in the results for synthetic data.

Table 2 presents the results. Due to the synthetic dataset, we observe many routes having equal scores. Therefore, the table reports the first 10 groups of routes, where each group represents a unique combination of the two high-level criteria (number of n-way intersections and frequency of right and left turns and non-turns). The results meet our expectations, as rank 1 group contains routes which comprise 4-way intersections only and show 2 right and left turns and 3 non-turns at DPs. While lower ranks in the table show the same distribution of intersections, rank 1 routes are the ones with the least euclidean distance to the best possible route. It is important to note that the euclidean distance reflects different degrees of deviations from the best possible route: The worst group, which is not shown in Table 2 consists of routes which have one 2-way and six 3-way intersections, 1 left or right and 6 non-turns. Similarly (also not presented in Table 2 for space reasons), routes with the same distribution (0,0,7) but with no left/right turns and 7 non-turns got a lower rank than routes with n-way distribution 0, 1, 6 and a more balanced distribution of actions at decision points.

Table 2 Results for scenario 1 where all nodes are of type I. Only the first 10 highest ranked groups of routes are shown in the table, some of which share a rank.

Rank	# Routes	# Intersections			# Turns		
		2-way	3-way	4-way	left	straight	right
1	7 635 056	0	0	7	2	3	2
2	6 341 188	0	0	7	2	2	3
	6 341 188				3	2	2
3	3 931 208	0	0	7	1	3	3
	3 931 208				3	3	1
4	3 808 196	0	0	7	1	4	2
	3 808 196				2	4	1
5	3 869 072	0	0	7	3	1	3
6	1 458 408	0	0	7	1	2	4
	1 458 408				4	2	1

Scenario 2

In scenario 2 the grid network now contains type I and type II nodes at a ratio of 9:1 (see Figure 1b). This induces variance in the data by including points-of-interest (POIs) as an additional high-level criterion, which comprises the number of POIs and the average uniqueness of a POI at a DP. Again, all high-level criteria are equally weighted. As no changes to the layout of the graph were applied, we expect routes with exclusively 4-way intersections to be higher ranked than those including also other types of intersections. In contrast to scenario 1, however, routes can now have a different number of type I and II nodes: As the average number of POIs per DP in all routes is 3.26 and the average uniqueness of POIs per DP equals 0.94, we expect routes with six type I nodes and one type II node to be higher ranked than other combinations of those types[5].

[5] This assumption is also backed up by the average number of type II nodes in a route which equals 0.61.

Table 3 Results for scenario 2. Only the first 11 highest ranked groups of routes are shown in the table, some of which share a rank. POI subdimensions are rounded to 2 decimals.

Rank	# Routes	# Intersections			# Turns			# Type II Nodes	Avg. # of POIs	Avg. Uniq. of POIs
		2-way	3-way	4-way	left	straight	right			
1	31 024	0	0	7	2	3	2	1	3.43	0.90
2	6 914 264	0	0	7	2	3	2	0	3	1
3	23 934	0	0	7	2	2	3	1	3.43	0.90
	23 934				3	2	2	1	3.43	0.90
4	5 743 264	0	0	7	2	2	3	0	3	1
	5 743 264				3	2	2	0	3	1
5	38 668	0	0	7	2	3	2	2	3.86	0.81
6	32 526	0	0	7	2	2	3	2	3.86	0.81
	32 526	0	0	7	3	2	2	2	3.86	0.81
7	14 160	0	0	7	3	3	1	1	3.43	0.90
	14 160				1	3	1	1	3.43	0.90

The results presented in Table 3 meet our assumptions. The highest ranked group represents routes which have only 4-way intersections, a balanced (close to global average) frequency going right, left or straight ahead at a decision point throughout the route, one type II node and the closest possible values to the global average regarding POI subdimensions.

Scenario 3

In scenario 3 we increase the variance in the data by changing the proportion of type I to type II nodes to 1:1, while keeping the graph layout unchanged (see Figure 1c). This means, scenario 3 simulates an area in which two 2 subareas are clearly different but have an equal share. The same high-level criteria as in scenario 2 are applied. As the frequency of n-way intersections and direction changes remain unchanged, we still expect routes with 4-way intersections only and a balanced frequency of right-, left- and non-turns at a decision point to be higher ranked. Given the 1:1 ratio of node types and the odd number of decision points (7), we expect routes with either three type I and four type II or four type I and three type II nodes to be ranked highest. These two combinations of type I and type II nodes are equally close to the global average for both POI subdimensions (avg. number POI: 4.5, avg. uniqueness POI: 0.66). The results for the third scenario are presented in table 4. In-line with our expectations, the highest ranked group has only 4-way intersections, a balanced (close to global average) frequency of (non-)turns and a balanced ratio between type I and type II nodes and, therefore, close to global average values for both POI subdimensions.

Taken together, the results of these three scenarios provide evidence that our approach yields reasonable results based on the controlled conditions of synthetic data. We will now continue with real-world data and the full set of criteria mentioned before (see Section 3).

5.2 Real World Example

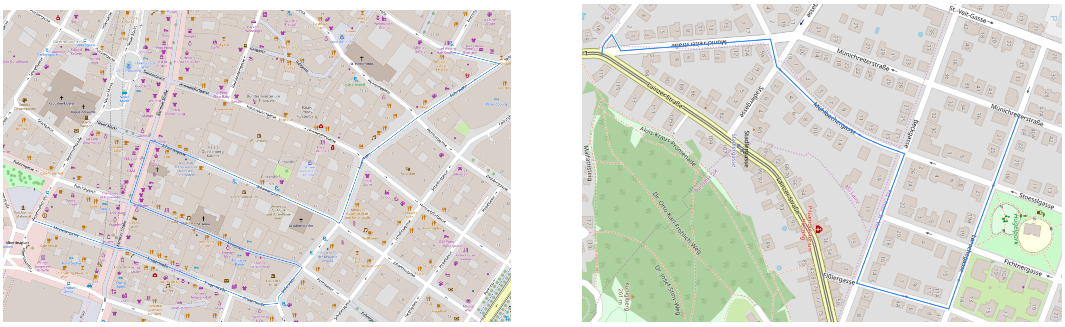
We have chosen two different areas in Vienna, Austria. Both regions significantly differ with respect to their degree of sealed soil, where Region 1 (located in the city center) shows a high degree and Region 2 (residential area) a low-medium degree of soil sealing (according to Urban Atlas 2012). We specified both pre-emptive criteria (see Section 3) and set the number of DPs to $k = 10$, and route length to a range between 1 000 m and 1 500 m. The length of possible routes in terms of both, the number of DPs and the distance, was chosen

Table 4 Results for scenario 3. Only the first 8 highest ranked groups of routes are shown in the table, some of which share a rank. POI subdimensions are rounded to 2 decimals.

Rank	# Routes	# Intersections			# Turns			# Type II Nodes	Avg. # of POIs	Avg. Uniq. of POIs
		2-way	3-way	4-way	left	straight	right			
1	37 092	0	0	7	2	3	2	3	4.29	0.71
	37 092				2	3	2	4	4.71	0.62
2	38 668	0	0	7	2	3	2	2	3.86	0.81
	38 668				2	3	2	5	5.14	0.52
3	28 310	0	0	7	2	2	3	3	4.29	0.71
	28 310				3	2	2	3	4.29	0.71
	28 310				2	2	3	4	4.71	0.62
	28 310				3	2	2	4	4.71	0.62

based on computation time (see Section 5.1). The underlying graph for Region 1 has 1 196 nodes, 1 740 edges and 4 290 636 possible routes of 12 points length (10 decision points plus start and end point which are not considered to be DPs). Of these routes, 62 294 have a length between 1 000 m and 1 500 m. The underlying graph for Region 2 has 498 nodes, 744 edges and 2 276 070 possible routes of 12 points length and 834 114 of these have a length between 1 000 m and 1 500 m. The observed difference in the number of considered routes is likely a result of the fact that the average segment length between two subsequent DPs in the city center area (Region 1, 2.25 km^2 area) is less than in case of the residential area (Region 2, 2.84 km^2 area).

For each region the closest to average route was calculated regarding the following 6 high-level and equally weighted criteria: *cardinality of decision points* (the number of n-way intersections on a route and the derived average options per DP), *frequency of right/left and non-turns*, *terrain* (proportion of negative, positive and zero slope), *POIs* (average number within a 10 meter radius and average uniqueness of category per DP), *regularity of DPs* and *type of environment* (land cover data). Figure 2 shows the routes for both regions which are closest to the best possible solution. Considering the above-mentioned criteria, routes from A to B achieve the same score as those from B to A. They only differ symmetrically in *slope* and *frequency of right/left and non-turns*. This symmetry causes an equal distance to the best possible route. Non symmetrical attributes like directed viewsheds would lead to a difference in score between route A to B and route B to A.



(a) **(b)**

Figure 2 The closest to average routes for Region 1 (a) and Region 2 (b) considering all criteria mentioned above (see Sec 3), which were equally weighted.

Table 5 Comparison between highest ranked routes and the best possible solution. Land cover classes are Urban Atlas classes: A (11100), B (11210), C (11220), D (11230), E (12100), F (12220), G (12230), H (14100) and I (14200). Land cover values do not sum up to 1 due to rounding. If there are two numbers for a feature this is due to having 2 winners for a region. Why the number of turns of best possible routes do not sum up to 10 is explained in the discussion.

Name	Avg. Options	# Intersec.				# Turns			Slope			Avg. # of POIs	Avg. Uniq. of POIs	Regularity				Land Cover %								
		3	4	5	6	l	s	r	neg	none	pos			3	4	5	6	A	B	C	D	E	F	G	H	I
Win. Reg 1	3.7	3	7	0	0	4/4	2	4/4	.05/0	.95	.05/0	.2	.2	55.68	16.31	NaN	NaN	.57	0	0	0	.09	.34	0	0	0
Best Reg 1	3.7	3	7	0	0	4	3	4	.03	.94	.03	.3	.17	51.97	17.24	83.2	69.34	.54	0	0	0	.09	.36	0	.01	0
Win. Reg 2	3.9	3	5	2	0	3/4	3	4/3	.03/.06	.91	.06/.03	0	0	57.75	19.86	72.80	NaN	0	.09	.48	.07	0	.36	0	0	0
Best Reg 2	3.9	3	5	2	0	3	3	3	.08	.84	.08	0	0	58.98	18.30	72.59	148.46	0	.06	.44	.07	0	.36	.01	.03	.01

Table 5 presents numerical results by providing figures for both, the highest ranked routes (will be referred to as *winners*) and the best possible solution, i.e., a hypothetical route which shows closest to average values for all criteria (will be referred to as *best*). Two aspects are important to be kept in mind: 1) The best possible solution does not need to be an actually existing route (see Sec 6); 2) there are two winners per region as each route can be traversed in both directions.

For both regions, the distribution of scores (i.e., the euclidean distance to the best possible solution) is similar (see discussion for an explanation of the maxima). The quantiles for the score in Region 1 are 0%: 0.2250, 25%: 0.5894, 50%: 0.7290, 75%: 0.8569 and 100%: 32.3001. The score quantiles in Region 2 are 0%: 0.1738, 25%: 0.5198, 50%: 0.6468, 75%: 0.8875, 100%: 5.2246. Regarding the *cardinality of DPs*, both winners in each region show a perfect match with best, respectively. With respect to *slope*, winners 1 are closer to best 1 than winners 2 are to best 2. It is vice versa regarding *POIs*, in which case winners 2 match best 2 perfectly (generally speaking, Region 2 is an area which is poor in POIs), whereas winners 1 have, on average, slightly less POIs at a DP than the best possible solution, but their uniqueness is higher. Looking at the *regularity of DPs* both routes reflect global averages very well if and only if they have this kind of n-way intersection[6]. Regarding *land cover* the differences between winners and best in both regions are minimal[7]. Regarding *frequency of right/left and non-turns* winners in Region 1 show one continuation less than the winner, whereas winners in Region 2 show either one left or right more than the best possible route. In both cases, the frequency of the best possible route is impossible to achieve (see Sec 6 below). Taken together, both winners in each region come close to the best possible route – which is hypothetical in this case and very unlikely to exist in general but reflects global averages as good as possible.

6 Discussion

In this work we propose and evaluate a systematic approach for the selection of pedestrian routes in a street network, with a focus on wayfinding experiments. As described in the related work section, a proper selection of street routes is crucial for several types of empirical studies. Such a systematic approach can help select a route based on a multitude of criteria and, furthermore, reduce the time necessary for manual selection. Moreover, the proposed approach can be seen as a step towards replicability of research, allowing to select a similar route at a completely different geographic location by exchanging the best possible solution

[6] NaN in a route are not contributing to the euclidean distance.
[7] If land cover does not sum up to 1 this is due to rounding.

with the target route of another location. The proposed approach was evaluated utilizing synthetic data serving as a ground truth. The results of this evaluation confirmed the validity and applicability of our approach. We performed a proof of concept evaluation using real data, once taken from the city center and once from a residential area in Vienna, Austria.

Two aspects of the results achieved for the real-world data need to be discussed in more detail: Firstly, the difference in distance between the the upper quartile and the maximum is very large for Region 1. However, the two routes (out of 62 294) having scores above 32 both have a 6-way intersection – a feature which is very uncommon for Region 1. Obviously, Region 2 has no large outliers as the maximum euclidean distance is far less than for Region 1. For both regions, however, the distances up to the upper quartile are numerically small; it is, therefore, a matter of future research whether these differences are meaningful for wayfinding research and with respect to which criteria this might be the case (see Section 7). Secondly, the fact that the best possible solutions do not match the predefined number of DPs by one needs in-depth discussion. All best possible solutions are calculated based on a z-score, which depends on the population mean and standard deviation. Due to the size of the population of possible routes, it is very unlikely that mean and standard deviations both are integers. The number of right, left and non-turns on an actual route (which is the third factor needed to calculate a z-score), however, must be integers. The figures need to be rounded (i.e., either floored or ceiled depending on the decimal digits), accordingly. In addition to that, the means of right and left turns must be symmetric. Hence, the best possible solution as a hypothetical route can show this anomaly of more/less (± 1) DPs than actually requested, whereas all actual routes in the population always have the predefined number of decision points (and turns). It is important to note that, although slope is a symmetric feature as well, its value can be decimal. Moreover, all other criteria are invariant to the direction of travel on a route. To conclude, our framework supports systematic and deterministic route selection for experiments considering weighted features provided by the researcher. Furthermore, exchanging the best possible solution with another target route (using this route as the average one) allows to find a similar route in a different place of the world.

The criteria utilized in this work served as an example and can be easily extended or even replaced by others. Of course, the more criteria used, the longer the route in terms of DPs, or the larger the search area, the more computation time will be required. In most cases, however, finding a reasonable route at the city level should be sufficient and this should be possible in less than one day of computing time as our results were. Our methodological framework allows to extend the list of criteria taken into account. Several aspects come to mind: the segment length and orientation might be worthwhile to be taken into account; if doing so, the number of POIs per segment of a given length may be worthwhile to take into consideration in order to study on-route landmarks (see [28]). Traffic data, flow of humans in an area and noise (e.g., stemming from factories) may have an impact on in-situ studies and might be considered, although it might be very difficult to obtain this type of data on a large-scale basis. While DPs per se have been extensively considered already, the order of turns (e.g., llrrslr) and the sequence of intersection types might be included (see e.g., [12]). One particularly important environmental feature, which is also missing due to unavailability of large-scale data, is the architectural style/diversity of buildings in a given area.

Computation time and difficulty of validating the results obtained from real data are the main limitations of this work. Concerning computation time, although this approach cannot be utilized for real-time purposes, most of the relevant cases for wayfinding will not be affected by that. Nevertheless, reducing computation time based on existing sub-graph search algorithms is already feasible (see Section 4), although this is out of the scope of our work. Results for real data are difficult, if not impossible, to validate. Synthetic data approaches for validation like the one presented above, however, ensure the validity of the results at least for the cases covered.

7 Conclusion and Outlook

The proposed approach can be considered as a valuable methodological framework, which can help to make informed decisions concerning route selections. As a consequence, this framework can partially support the design of experiments and enhance replicability.

The results of the presented approach strongly rely on the availability of appropriate data sources. The availability of pre-computed data, such as DP type and regularity [10] are crucial for lowering the required computational costs. As a consequence, we will follow the path of open data and pre-compute several features that might be relevant for route selection. Furthermore, we plan to provide an API[8] that will ease the access to our framework and allow to compute a winner route with minimal effort.

Although for most cases only the best result (i.e., the winner route) is relevant, there might be cases were the comparison between routes is of interest. Therefore, it is reasonable to study whether the Euclidean distance is actually justifiable by means of empirical results: The distance metric chosen should reflect empirical results, i.e., if participants are subject to routes which differ more, less comparable results should occur and vice versa. We are going to conduct within-group design wayfinding studies on this problem.

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