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Are routes aligned with the street network less complex? A comprehensive analysis

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Abstract. The routes displayed on maps by navigation support systems are intended to help users to orient themselves towards reaching the destination and to infer information related to their navigation. Inferring how complex a route is, including how well you think you can remember it and the likelihood of getting lost, may influence expectations on how it is navigated. However, it is not well understood when and where a route displayed on a map is perceived as complex and why someone perceives it this way. Current methods for assessing complexity tend to focus either on (i) the complexity of the route or on (ii) the complexity of the environment as a static and global property. By taking inspiration from navigational map reading and how routes and street networks are perceived on a map, this paper investigates how environmental complexity influences route complexity and length. We developed a new approach to gauge the alignment between the orientation of a route's origin and destination with respect to the orientation of the streets within the network, and we investigated how this measure relates to route complexity and length.

Submission Type. Algorithm, Dataset, Analysis.

BoK Concepts. AM11 Network Analysis, CV6 Usability of Maps

Keywords. simplest path, shortest path, route complexity, simplest route, shortest route, navigation, wayfinding, origin-destination, grid-likeness, street network, alignment.

1 Introduction

The display of routes between locations on a digital map is one of the many ways modern navigation support systems can help users. As a representation of how two locations are connected to each other, it can support building a mental map of the environment and inferring information about it (Zhang et al., 2014). Its main purpose is to be followed (with or without instructions) or to inform planning by showing time and traffic estimates or alternative public transport modes (Topete et al., 2024).

Research on environmental complexity has identified several different factors that influence the ease with which we learn and navigate different environments. In researching the environmental complexity of buildings, Gärling et al. (1986) developed a conceptual framework of environmental complexity that includes the following: the degree of *architectural differentiation* i.e., the visual similarity of different parts of the environment; *Visual access*, i.e., the extent to which you can see other parts of the environment within it; the complexity of the *layout*, i.e., the size and number of possible routes in an environment. Layout complexity is measured as the density of interconnections between decision points (ICD) by O'Neill (1991) who found that buildings with a higher ICD was correlated with less accurate cognitive maps and poorer navigation performance. In a similar study, Li and Klippel (2012) employed space syntax to model a library's visibility, layout complexity (ICD), and connectivity, noting higher pointing task errors when participants were in regions with high layout complexity and low visibility and connectivity.

Environmental complexity has also been researched as a factor influencing the ease with which we navigate different routes in an environment. Including the branching factor at the intersections that a route visits, and the availability of landmarks, signage, and other features that can allow for simpler instructions and wayfinding (Giannopoulos et al., 2014a).

Properties linked to the complexity of routes and environments are also related to their perceived complexity. Weisman (1981) discovered that disorientation is less frequent in buildings where the layout is seen as simpler. Routes that change direction more frequently are also perceived as more complex (Horned et al., 2024; Schwartz-Chassidim et al., 2014a), and require complex instructions (Klippel et al., 2003). Similarly, maps of street networks that are more densely interconnected are also perceived as more cluttered (Schwartz-Chassidim et al., 2014b).

When judging how complex a route is, human map readers appear to judge the complexity of routes differently from what computational models estimate as complex in the route and environment (Horned et al., 2024; Tang et al., 2020). The route is perceived within the context of the surrounding environment displayed on the map, including how the origin and destination are connected and oriented within the environment. This includes the orientation and alignment of the streets with the route and other linear features such as rivers or district boundaries (Lynch, 1960, p.62). In addition, map readers can perceive the route in relation to features of the street network. Research in spatial cognition shows that humans perceive geometric regularity and complexity (Campbell et al., 2024), and that 4-year-old children have already an informal awareness of parallel relations (Sinclair et al., 2013). So one might expect that routes on a grid with parallel lines might be more intuitive for users.

Alignment has been studied as a factor influencing environmental learning and spatial memory (Tang et al., 2020). Alignment has often been measured in terms of how much you need to rotate yourself, a real/sketch map, or a perspective for them to match or partially match. In a laboratory experiment by Aretz and Wickens (1992) they found that mental map rotation involves two sequential rotations: First, rotating the map to align it with your egocentric frame of reference (e.g., matching the map with your forward view); and then rotating the map to align it with an external frame of reference (e.g., matching North on the map with North in the environment). However, the participants shifted to an analytical strategy for matching the map with more complex environments. Alignment also affects navigation performance when an environment is learned by reading a map, reducing performance when not aligned to the orientation from which the environment was learned (Richardson et al., 1999). You-are-here maps (Levine et al., 1982) show another example of alignment effects, where the map is more easily comprehended if the perspective of the map-reader is aligned with primary axes of the map (e.g., up on the map is forward to the map reader).

The street network is one of many potentially competing external frames of reference that can influence spatial memory and navigation (Werner and Long, 2003). For example, Montello (1991) found that people stopped on streets that are misaligned with respect to the angularity/orientation of streets in the local environment made larger errors in pointing to cardinal directions and local landmarks. The degree of parallelity and alignment of streets with each other was studied by Boeing (2019) who developed an entropy-based measure of how ordered a street network is in relation to other aspects of street network complexity (Boeing, 2018).

So far, most research on alignment effects has concerned users navigating or orienting themselves within an environment, but not from a map reading perspective. From this perspective, the layout of the street network, potential landmarks for navigation, and how they are configured in relation to a destination are made visible. Moreover, alignment is one of the ways in which the street network complexity of the environment can interact with route complexity.

2 Methods

This study investigates different factors that can influence the complexity of a route as calculated by the shortest and simplest path algorithms (Duckham and Kulik, 2003). Most importantly, we analyze whether and to what extent the *alignment* of the bearing of the direct line between an origin and a destination with the predominant bearing of the street network impacts route complexity. As a further factor, this impact may be affected by how grid-like the street network is. In addition, we look at how two simpler measures, the density of intersections and the average node degree (or InterConnection Density by O'Neill (1991)), relate to our findings. We performed this analysis following these steps:

1. Determining origin-destination pairs.
2. Finding the shortest and simplest route from an origin to a destination.
3. Truncating the graph and calculating the average node degree and intersection density.
4. Assessing the grid-likeness of the street network.
5. Computing the alignment with the street network.

The methods applied at each step are described below.

Step 1. Determining origin-destination pairs and routes between those.

As a starting point, we use the 100 cities listed in Boeing (2019). We use Overpass to download the road network of these cities from OpenStreetmap, with the city name and the predefined network type “drive” as a query. Road networks are analyzed as multidirected graphs using OSMnx in Python (Boeing, 2024). Furthermore, road networks are simplified only by retaining nodes at intersections, and all parallel directed edges are removed except the edge with the shortest length. Then, three random nodes are selected in each city as origin locations for our origin-destination pairs.

To find possible destinations for every origin, we first find all nodes within a 10% margin of 4000 meter distance away from the origin (i.e. 3,800–4,200 meters) to ensure we find a large enough sample of nodes in all directions. At this point, the number of possible destinations around an origin can range from below a hundred nodes to thousands. To avoid having some of these origins and cities skew the data, we create a smaller sample. The possible destinations are divided into 36 bins according to their bearing from the origin. Then nodes are added to the sample by cycling through the bins and picking a node at random, beginning each cycle at a random bin, and stopping if 18 bins in a row are empty or if 144 nodes are found (see Fig. 1 for an example). These form the origin-destination (OD) pairs for our further analysis. This is done to ensure that the selected destinations are representative of all bearings around an origin in all environments.

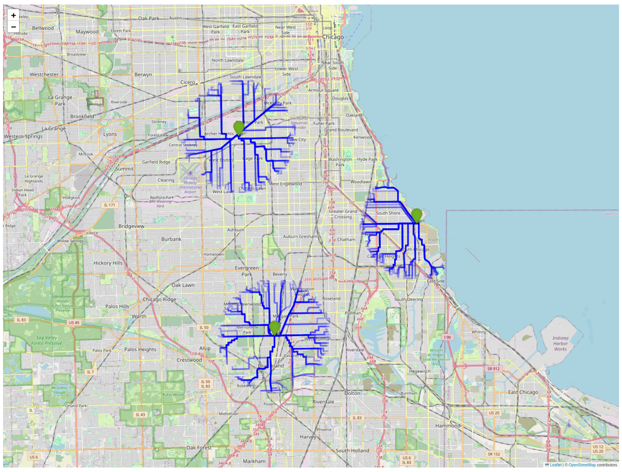

Figure 1. Three random origin locations in Chicago and the shortest path to a sample of 144 nodes within a distance of 3,800 and 4,200 nodes meters away.

Step 2. Finding the shortest and simplest route from an origin to a destination.

For each origin-destination pair, we find the shortest and simplest route. The shortest route is retrieved using Dijkstra with the distance between the nodes as the cost of the edges. The simplest route is computed using the algorithm described in Duckham and Kulik (2003). The complexity in this algorithm is a cost that is derived from edge pairs and the kind of turn that takes place moving from one edge to the next following the rules displayed in figure 2. As an example, the complexity of turning in an intersection with a node degree greater than two is calculated as $5+deg(v)$, unless it is a turn after entering a T-intersection that has a static cost of 6. Later, we use the same turning costs to measure and compare the complexity of the routes, as the number and complexity of decision points are linked to route complexity (Giannopoulos et al., 2014b).

Step 3. Truncating the graph and calculating simpler environmental complexity.

After both the simplest and the shortest route have been obtained for an origin-destination pair, we truncate the graph to contain the part of the street network that is "between" the origin and destination, and not necessarily the part of the street network that the routes travel through. All the edges contained in (or intersecting) a square surrounding the OD pair are kept, which is a polygon defined by the points of the origin and destination together with the points of a perpendicular line intersecting the first line

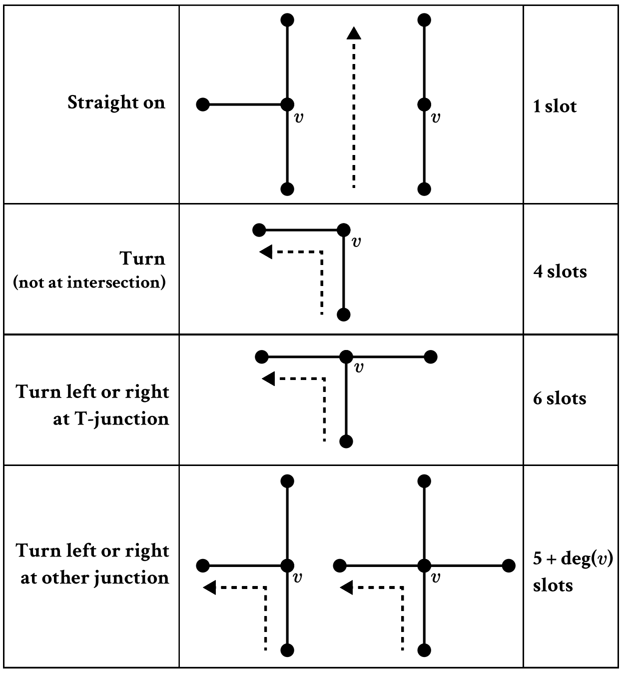

Figure 2. Diagram showing the cost of turns at different types of intersections, adapted from Duckham and Kulik (2003).

at its midpoint. In this rectangle, we calculate the density of intersections (number of nodes relative to area of the rectangle in km^2), along with the average node degree.

Step 4. Assessing the grid-likeness of the street network.

Next, we measure how aligned OD pairs are to the street network in the truncated graph. Both network and origin-destination bearings are added to a distribution with 36 equally sized bins each representing 10°, with the first bin beginning at 355°. The bearing from the origin to the destination and its reverse bearing are calculated on the basis of their coordinates in an appropriate UTM projection.

In order to create a distribution of bearings in the street network, the bearings of the streets are computed as the forward and reverse bearing of all edges in an undirected version of the graph, along with the length of the edge as a weight for bearings in the distribution. Furthermore, the entropy of this distribution is calculated and then normalized to compute a score indicating how grid-like the street network is following Boeing (2019). Both distributions are normalised by the total number of bearings so that the density of the bearings can be compared in later steps.

Step 5. Computing the alignment with the street network.

To determine how aligned the origin-destination bearings are to the bearings of the street network, the two distributions are compared using fast Fourier transform cross-correlation. The alignment between the two distributions is then measured as the number of steps one distribution needs to be rotated to find the strongest, closest correlation. This is found by penalizing the correlation by the number of steps divided by the maximum number of steps. As an example, an OD pair in a very grid-like city is aligned with the network if the strongest correlation is found at a rotation of 0, ± 9 or ± 18 bins (i.e., a difference of $0°$, $90°$ or $180°$). If it is slightly misaligned in the grid, as shown in Figure 3, the closest and strongest correlation is found at 2 counterclockwise steps, with equally strong correlations at 7, -11, and 16 steps, but receiving a higher penalty.

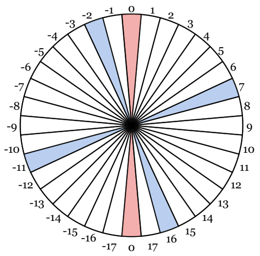

Figure 3. Visualization of an example: the bearings of the origin-destination (OD) pair are red, and the bearings of the street network are blue. The alignment score of the OD pair here is 2, since this is the closest and strongest correlation.

3 Results

This section presents the results of our analysis regarding how the alignment of OD pairs may affect the complexity of the route, given the complexity and grid-likeness of an environment.

3.1 The Dataset

Across all cities, a total of $34,192$ origin-destination pairs were selected, and after removing outliers identified as pairs with a complexity or length above the median of the third quartile, a total of $29,579$ OD pairs were left, which we use for computing shortest and simplest paths. The mean complexity for the shortest route was $\mu = 101$ (Std. Deviation: $\sigma = 38$), whereas for the simplest route it was $\mu = 66$ ($\sigma = 19$). We normalized the complexity of the routes by the maximum route complexity.

The environments surrounding each route were grouped into 5 categories depending on their grid-likeness, from *low* to *very high*, which is calculated based on the street orientation entropy. Almost half of the street networks fell into the low grid-likeness category as Table 1 shows, which is comparable to previous findings by Boeing (2019). We also found that the level of grid-likeness in the truncated street networks can vary greatly between OD pairs within the same city. For example, between the 332 pairs selected in Baghdad, the grid-like value ranges from 0.15 to 0.91.

The distribution of OD pairs across alignment scores is shown in Table 2 and it ranges from 0 to 8, with an alignment score of 1 being the most common.

Table 1. Distribution of OD pairs across different grid-like groups in our dataset which follows a logarithmic function.

Grid-likeness	thresholds	Pairs	% of Total
low	$[0.0, 0.2)$	$14,579$	49.1
medium	$[0.2, 0.4)$	$4,763$	16
high	$[0.4, 0.6)$	$4,360$	14.7
very-high	$[0.6, 0.8)$	$3,396$	11.4
extremely-high	$[0.8, 1.0)$	$2,610$	8.8

Table 2. Frequencies and percentages of alignment.

Alignment Score Levels	Counts	%ofTotal
0	3,177	10.7
1	4,094	13.8
2	3,837	12.9
3	3,713	12.5
4	3,345	11.3
5	3,128	10.5
6	2,955	9.9
7	2,875	9.7
8	2,584	8.7

3.2 Route complexity analysis

We investigated how alignment is related to the properties of the route. Beginning with complexity, within each grid-likeness group, we checked for differences in complexity of the shortest and simplest route across different levels of alignment (Table 2). An ANOVA of the complexity of the shortest route between different levels of alignment indicates that there are significant differences between the levels in all grid-like groups except for the most non-grid-like group. A post-hoc analysis shows that levels 4 to 6 are significantly more complex than levels 0 and 8 (with the strongest mean difference being 0.1). For the simplest route, an ANOVA indicates that there are some significant differences between the alignment levels in the *very-high* grid-like group (i.e., $[0.6, 0.8)$) with the strongest mean difference being 0.02.

To compare how the length of a route is related to alignment, we calculated the circuity of the route as the length of the route divided by the direct-line distance between the origin and destination in meters. Figures 6 and 7 show that the circuity of the routes has an inverse u-shape relationship to the alignment level of the OD pairs.

3.3 Environmental complexity analysis

In order to investigate how environmental complexity relates to alignment, we computed the Pearson correlation coefficient between the complexity of the routes and diverse measures of environmental complexity, starting with the average node degree.

We found that the shortest-route complexity has a significant negative correlation with the average node degree of the street network ($r = -0.119$, $p < .001$), indicating

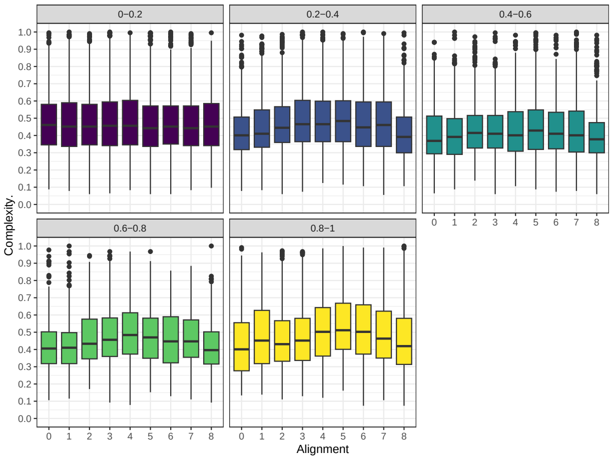

Figure 4. The shortest-route complexity at different levels of alignment across increasingly grid-like street networks. Each subplot shows results for a specific grid-likeness group, starting from *very-low* to *extremely-high*. The complexity of routes for each alignment score level (0-8) are shown within each group.

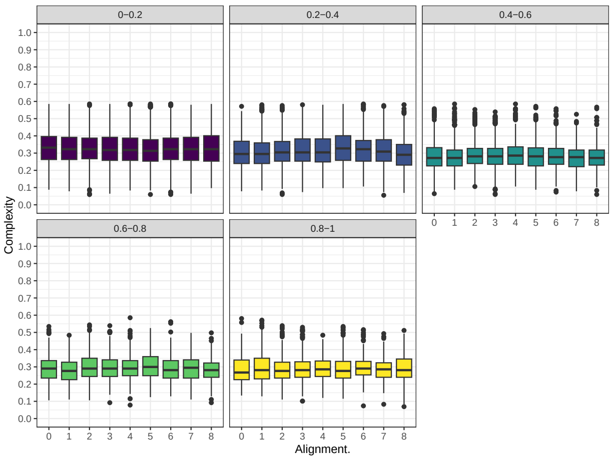

Figure 5. The simplest-route complexity at different levels of alignment across increasingly grid-like street networks.

that as the average node degree increases in the network, the complexity of the route slightly decreases. The simplest route also has a slightly stronger negative correlation with the average node degree ($r = -0.26$, $p < 0.001$). Moreover, we computed the Pearson correlation between the complexity of the routes and the intersection density and we obtained that the intersection density is positively correlated with the complexity of the shortest route ($r = 0.453$, $p < 0.001$), and it also has a positive correlation with the complexity of the simplest route ($r = 0.451$, $p < 0.001$). Moreover, there is a positive correlation between the grid-likeness of the street network and the average node degree ($r = 0.469$, $p < 0.001$).

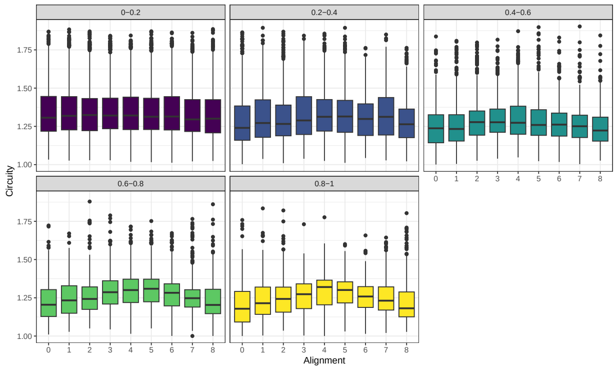

Figure 6. The circuity of the shortest route at different levels of alignment across increasingly grid-like street networks.

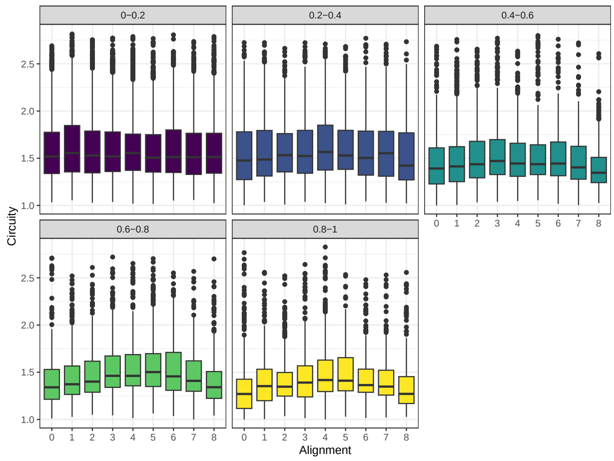

Figure 7. The circuity of the simplest route at different levels of alignment across increasingly grid-like street networks.

4 Discussion

In this study, we investigated a potential relationship between how (well) an origin-destination pair aligns with a street network and its corresponding route's complexity, moderated by the network's grid-likeness. To this end, we compute the distribution of bearings of the street network, and then compute how well the OD pair fits this distribution by finding the closest, strongest correlation. The results demonstrate that this method of measuring alignment is related to a difference in route complexity and length in street networks that are grid-like, but not in the majority of street networks that are not grid-like (compare Figures 4 and 6).

In the street networks that are grid-like, we can observe that alignment has a significant effect on the complexity of the shortest route in particular. In perfectly symmetric grid-like street networks the shortest route and the simplest route would be equivalent in length. Therefore, the effect of alignment on the shortest route but not the simplest route in grid-like street networks implies that there are irregularities that make a more “diagonal" route involving more turns shorter. It also highlights the capability of the simplest path search algorithm in finding a simpler route than the shortest route when the destination is misaligned with the grid. With decreasing grid-likeness, the bearing distribution resembles more and more a uniform distribution, i.e., there is a decreasingly less pronounced main orientation in the network. Therefore, increasingly any bearing of an OD pair becomes a 'good fit' for the given bearing distribution as differences in the correlation strength between rotation steps become smaller and smaller. In other words, it becomes increasingly less useful to even talk about alignment in such networks since they lack a clear global structure–at least one captured in a bearing distribution.

We found no indication that the environmental measures (i) intersection density and (ii) average node degree interact with alignment and, thus, may adequately capture route complexity. A higher average node degree is correlated with less complex routes, but it also acts as an indicator that the street network is more grid-like (four-way intersections are more common in grid-like street networks) in which the routes tend to be less complex.

Here we have looked at the orientation of the OD pair within the street network as the primary direction, which may be more or less aligned with the street grid. In that, we took inspiration from spatial cognition research. As a computational method, further research is needed to assess how accurate or useful alignment is as a heuristic for predicting route complexity, considering different linear features in the environment. Additional user studies are required to investigate if alignment has any effect on the perceived complexity of a route; and whether routes aligned with the grid are perceived as more intuitive than misaligned routes.

Other research indicates that people segment the route and remember it as different segments in a physical or mental map (e.g., studies on taxi drivers by Griesbauer et al. (2025)). To take this into account, one can consider the alignment of different segments of the route with the street network, and to this end the route could be further abstracted to the segments between the route-defining locations of the route (Teimouri and Richter, 2022).

The analysis in this paper examines the alignment with the street network, whereas there are other studies in the literature that consider the alignment between the map-reader direction and the map orientation or the alignment of the perceived structure. A future research direction would involve an exhaustive assessment of possible perceived alignment including other visual elements with direction, such as water bodies (e.g. rivers), green areas (e.g. parks) and/or the orientation and shape of buildings and neighborhoods –and depending on the context of the map reader– also the direction they are facing in the environment and the primary axes of the local environment they are in.

Availability of data and software

The underlying geographic data used in our analysis were downloaded from OpenStreetMap (https://www.openstreetmap.org) on January 15th 2025, using the Overpass API (https://wiki.openstreetmap.org/wiki/Overpass_API), the OSMnx package v2.0.1 for graph creation and analysis (https://osmnx.readthedocs.io/en/stable/), and the PyProj package for coordinate projection (https://pyproj4.github.io/pyproj/stable/index.html).

The acquired dataset (after removing outliers) and additional tables can be found on OSF here https://osf.io/u8k5m/?view_only=23bc67c23f6f4f3094d937e08fd1a5f6. The different data pre-processing, route calculation, and alignment computation steps have been implemented in Python, which can be found at https://github.com/ArvHor/perceived-route-complexity/tree/agile-2025, where scripts for rerunning the statistical analysis are also provided..

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