Navigating Your Way! Increasing the Freedom of Choice During Wayfinding

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Abstract

Using navigation assistance systems has become widespread and scholars have tried to mitigate potentially adverse effects on spatial cognition these systems may have due to the division of attention they require. In order to nudge the user to engage more with the environment, we propose a novel navigation paradigm called *Free Choice Navigation* balancing the number of free choices, route length and number of instructions given. We test the viability of this approach by means of an agent-based simulation for three different cities. Environmental spatial abilities and spatial confidence are the two most important modeled features of our agents. Our results are very promising: Agents could decide freely at more than 50% of all junctions. More than 90% of the agents reached their destination within an average distance of about 125% shortest path length.

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1 Introduction

Adaptive route instructions for pedestrian wayfinders have seen considerable research interest [7]. At the same time, empirical evidence has been collected which suggests an adverse impact of wayfinding assistance systems on spatial cognition and knowledge acquisition (see e.g., [6]). Routing paradigms which allow wayfinders to make an increased number of decisions and, therefore, reduce the number of instructions given as much as reasonable would be one option to remedy this effect. We explore one possible solution to this problem and propose a pedestrian navigation paradigm which balances the number of given instructions and the freedom of choice left to the user at junctions. We explore the feasibility of this paradigm by means of an agent-based simulation. At the start, an agent is provided with a destination vector, similar to someone pointing to the destination when asked for instructions. Once an agent started walking they do not need to stick to a predefined route, hence they will not suffer from *on-route uncertainty* [22] but are free to make their own decisions at junctions. However, a route instruction will be provided if odds are increased that an agent, based on its current state, is likely to choose a not reasonably good branch at a given junction. The presented paradigm aims for less instructions and more free choices along the route – regardless the way instructions are phrased or the modality they are given in.

Based on a comparison of our routing paradigm (labelled *free choice navigation – FCN*) to the turn-by-turn (TBT) technique, which is prevalent in commercial wayfinding assistance systems, our contribution is threefold:

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1. We present a new navigation paradigm (*free choice navigation*);
2. We provide evidence that agents reach their destinations within a reasonable departure from the length of the shortest path using our approach and
3. We quantify the number of instructions we save/add compared to the baseline (TBT).

Successfully testing of our approach has a potentially important implication: Reducing the number of instructions would provide users of wayfinding systems with more time to observe the environment while, simultaneously, forcing them to engage more with it as they have to make their own decisions. Based on prior evidence (see e.g., [33]), this is expected to result in increased spatial knowledge acquisition (see section 7 below). It is important to note, though, that our approach is meant to be used in a leisure scenario, i.e. in situation in which wayfinders do not feel any time pressure.

2 Related Work

Given our research goal, we discuss three different branches of related work. First, literature on reducing the number of TBT navigation instructions or adapting their structure/presentation is reviewed. Second, we discuss literature using the beeline/as-the-crow-flies navigation approach. Lastly, we review agent-based simulations modeling pedestrian behavior. Taken together, this review reveals important factors which need to be considered when modeling agents and its accompanying mechanics (see also Section 4).

2.1 Enhancing TBT Instructions

In recent years, evidence has been collected which suggests that the use of navigation systems may have an adverse impact on spatial cognition and orientation (see e.g., [6, 21]). This effect is commonly explained by the need to divide the attention between the navigation system and the environment when following a pre-determined route (see e.g., [13]). Possible remedies regarding TBT navigation systems are enhancing instructions with additional information (see e.g., [16, 36]), reducing the number of instructions [28], combining them with different interaction techniques (see e.g., pointing [25]) or providing haptic or audio feedback (see e.g., [12, 14]). All these approaches assume a predefined route. This is in contrast to our paradigm according to which users can make their own spatial decisions to a large extent.

2.2 Beeline Navigation

There are alternatives to TBT navigation approaches, e.g., using the beeline to the destination. One particularly important idea is the so-called least-angle strategy, which was for the first time thoroughly studied by Hochmair and Frank [20] using a simulation study. According to this strategy a user chooses the option with the least angle with respect to the (believed) destination vector. The least-angle strategy has been studied with respect to various implementations: [29] and [8] report on prototype navigation systems for pedestrians which use vibro-tactile feedback devices to indicate the beeline. Either system guides users successfully to their destination. Both systems allow for free exploration but none of them control for an upper path length limit. This is in contrast to our approach: We try to find a compromise between free exploration and maximum path length while determining the point in time at which an instruction needs to be given. Savino and colleagues [30] compare TBT and two different implementations of the beeline approach for cyclists, one of which provides visual cues when the beeline differs from the shortest path branch. The latter approach enhances user confidence. The beeline approach was preferred for leisure scenario. This is in line with prior evidence suggesting that it is important for pedestrians to optimize both, distance and angle [31] and that the environmental complexity [15] has also a major impact on route choice behavior. Our approach takes these findings into account (see Section 4) by providing the beeline at the starting point and providing further wayfinding assistance as needed.

2.3 Simulation Studies and Models of Pedestrian Behavior

As mentioned above, the beeline approach was studied by Hochmair and Frank [20] using a simulation study regarding perception errors. Based on this work, Hochmair [19] analyzed the effectiveness of the least-angle strategy with a simulation study for different transportation modes. The results suggest a limited usability of this approach in real life (human perception and memory errors). Our simulation takes these findings into account by modeling human errors and actively supporting the user if help is needed, moreover, it incorporates environmental spatial abilities and spatial confidence (see Section 4). Other agent-based wayfinding studies frequently focus on collision avoidance (see e.g., [35]), on evacuation (see e.g., [37]) or on the interplay between navigational instructions, the environment and the agent (see e.g., [34, 22]), including research on route choice behavior based on different levels of cognitive maps [10]. Generally speaking, the findings of these papers are based on the assumption that a path a user should follow exists. Again, this is in contrast to our approach. Neither do agents receive an instruction at every decision point, nor is there a predefined path. Our agents are also not equipped with prior knowledge of the environment nor do they know the true destination direction at every junction (which is in contrast to, e.g., the models used by Kneidl [23]), i.e., they are considered to be unfamiliar and, hence, have no cognitive map.

3 Simulation Preparation and Baseline Condition

In order to test[1] our hypotheses (see Section 5) we run an agent-based simulation (non multi-agent) with two conditions. The main focus lies on whether agents do reach their destination with our approach. Consequently, we will not model effects on spatial cognition, e.g. spatial knowledge acquisition as this aspect will be scrutinized in a real-world study (see Section 7). The simulation study was run in three cities with three different network types [32], namely Djibouti City (Djibouti, type: *irregular*), Vienna (Austria, type: *high transit*) and Mexico City (Mexico, type: *checkerboard*). For each city 100 random routes with a length ranging between 500m and 5000m were chosen in order to test the approach on shorter and longer routes. We tested two conditions (*TBT* vs. *free choice navigation*): Each condition was tested with 3000 agents, i.e., there are 6000 different agents (between subject design). The agents are constructed based on the the so-called BDI-framework [27] for practical reasoning: The agents simulate pedestrians who have **B**eliefs about where their destination is located; agents **D**esire to reach their destination; and, finally, they act based on **I**ntentions, i.e., at each intersection they reason about which decision they need to take in order to reach their goal based on their beliefs.

3.1 Software and Data

Several agent-based modeling and simulation frameworks exist [1]. For our approach we utilized python 3.8.8 using the package networkx (v2.5.) [17], avoiding frameworks providing graphical interfaces since this was not relevant for the presented study. The raw network

[1] The terms *junction* and *intersection* are used interchangeably, as well as *option* and *branch* are.

data were downloaded from OpenStreetMap (OSM). The intersections were calculated with the Intersections Framework [11], whereas street segments were extracted with a custom script. With those components each city could be represented as a networkx graph.

3.2 Following Navigation Instructions

In this subsection the modeling aspect which is shared across both simulation conditions, is explained: In either condition an agent has the ability to follow navigation instructions. This ability (*nav_instr*) is modeled using a value in the range $[0.8; 1.0]$ and represents the probability of taking the branch indicated in the route instruction. This ability is expected to be high because navigation instructions are followed on a daily basis by millions of users, hence the interval between $[0.8, 1.0]$. We use a uniform distribution in case of the baseline, whereas a normal distribution is assumed in case of our *free choice navigation* approach (see Section 4).

3.3 Baseline

The baseline our approach is compared with is a TBT navigation system, i.e., agents receive navigation instructions only at turning points. Agents in this condition have a single attribute called *nav_instr* which represents their ability to follow a route instruction correctly. It is represented as a value within $[0.8; 1.0]$ drawn from a uniform distribution, because no figures were found on how well people can follow turn-by-turn navigation instructions in general (i.e., a mean value based on empirical grounds is not available).

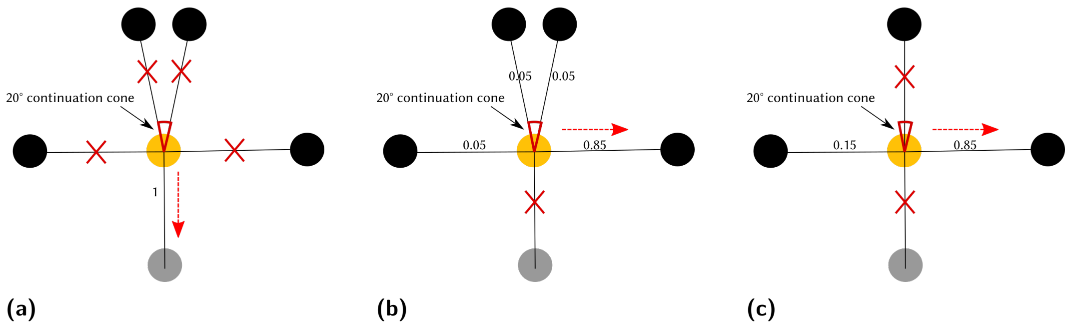

Figure 1 The decision mechanism for the baseline condition. current node: yellow (in the center); previous node: grey; given instruction: red arrow; excluded branches: red cross; annotations represent the probability of a branch to be taken: (a) turn-around instruction (always performed correctly); (b) Sample turn instr. 1 with two straight ahead options; (c) Sample turn instr. 2 with only one straight ahead option.

There are three options for an agent at any junction: **(1) no instruction** means continue straight ahead (within a 20° cone); **(2) turn-around instruction** which are always followed correctly (see Fig. 1a); **(3) turn instruction** which is interpreted as a weighted random choice (see Fig. 1b and 1c). The decision which segment is taken is modeled as a multi-step process, which starts only if a turn instruction is given: First, all potential options to follow are identified. This means, the option the agent is coming from is excluded because it would have been otherwise a turn-around instruction. If there is only one straight ahead option, it is also excluded too (see Fig. 1c) because no instruction would have been given if continuing straight would have been the correct option. Next, probabilities are assigned to each option: The agent's ability to follow navigation instructions (*nav_instr*) is assigned as a probability to the option which is indicated as correct by the turn-instruction. All other n remaining options have a probability of $\frac{1-nav\_instr}{n}$. Finally, given these probabilities a weighted random choice is performed and the agent moves to the next junction and the procedure is repeated until the agent reaches its destination.

4 Free Choice Navigation Approach

In this section, a detailed account of the *free choice navigation* approach will be given. We, first, describe the properties of our agents and then, we move on to explain the decision mechanism of our agents in detail. In order to mitigate potentially adverse effects on spatial cognition by the usage of wayfinding assistance systems (see, e.g., [21]) we propose the *free choice navigation* approach. This paradigm nudges users to engage with the environment by balancing the number of free route choices against a given maximum distance threshold.

4.1 Agent Properties

Due to the nature of our approach, modeling the agents is more complex than in the baseline condition. Agents have five different properties, each of which is detailed below:

Belief Vector (*belief_vec*) represents a subjective vector from the current junction to the believed location of the destination which, in turn, depends on the agent's current orientation. In contrast, the true destination vector ($true\_dest\_vec$) is the beeline from the current junction to the true destination location. These two vectors usually differ (see [20] for this claim and Figure 3 for an example).

Environmental Spatial Abilities (*env_sp_ab*) follow a normal distribution ($M = 0.5$, $SD = 0.2$; co-domain $[0; 1]$). They have an impact on the belief vector. They are needed to "form a coherent mental representation" of the environment [39]. To the best of our knowledge, there is no evidence about the distribution of Environmental Spatial Abilities, therefore we assumed a normal distribution.

Spatial Confidence (*conf*) refers to an agent's confidence [39] about the destination direction ($[0.0; 1.0]$). Prior evidence indicates (see, e.g., [26]) that self-reported tests on spatial abilities have been a good performance predictor. We, therefore, model an agent's spatial confidence based on it's environmental spatial abilities: It seems to be plausible to assume that agents which are good wayfinders would indeed have a high self-confidence in knowing the destination direction. Therefore, the maximum (max_conf) and minimum (min_conf) confidence level of an agent are related to env_sp_ab and are set to $env\_sp\_ab \pm 0.2$ (co-domain $[0; 1]$).

Ability to Follow Navigation Instructions (*nav_instr*) represents the ability to follow a navigation instruction (see [34]; see also baseline agents). For this condition it is equal to $env\_sp\_ab * 0.2 + 0.8$; in order to have the same range as for the baseline condition.

Memorized Dead Ends Agents are able to remember dead ends they have already taken in order to avoid back and forth movement (see [19]).

4.2 Initializing Agents

Before an agent starts a trial, both, its environmental spatial abilities (env_sp_ab) and its initial spatial confidence ($conf$) value are randomly set according to the intervals described above. Additionally, information about the destination direction is obtained, i.e., $belief\_vec$ and $true\_dest\_vec$ are pointing to the same direction. In each city the same population of agents is used. A trial is considered successful if and only if an agent has reached the destination deviating no more than a predefined threshold from the shortest path length.

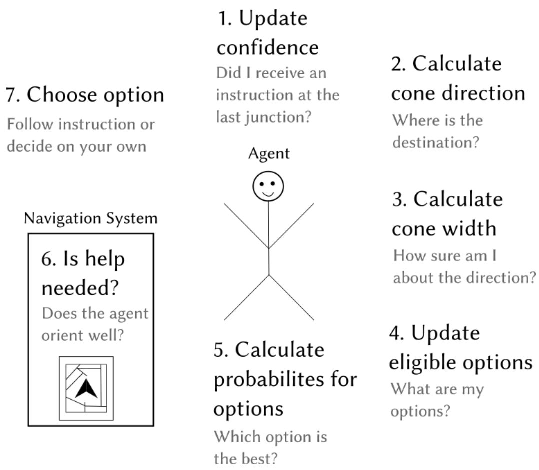

Figure 2 Overview of the decision mechanism for the *free choice navigation* condition.

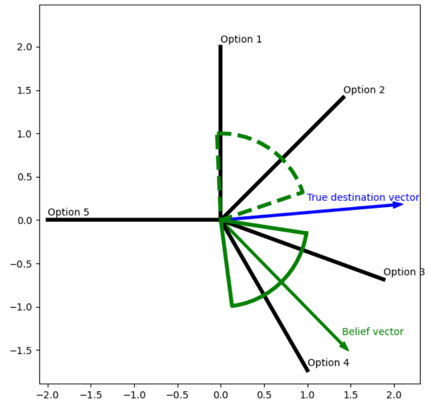

Figure 3 The agent will consider options 3/4 (branches intersect green solid line polygon). The dashed polygon represents the alternative cone (see step 2).

4.3 Decision Mechanism

The key geometric object we use to implement the reasoning of an agent at each intersection is a *cone*. This polygon represents where the agent believes the destination lies in (see Figure 3). The width of the cone ($cone\_width$) represents how certain an agent is about $belief\_vec$. It is, hence, influenced by nav_instr, $conf$ and environmental complexity (env_comp, see below) and ranges between 360°(total confusion) and 1°(very sure).

Figure 2 provides an overview of the reasoning steps an agent and the simulated navigation system (only step 6) execute. It is important to note that this process will start if and only if the current node is not the goal node nor the current traversed path length is equal or greater than the maximum allowed path length. In both cases the trial would end immediately.

Having said this, the reasoning process starts with the update of the spatial confidence (step 1), based on whether an instruction was issued at the previous junction. Step 2 focuses on the update of its assumption about where the destination is located at. In Step 3 the certainty about this belief vector is modeled. Steps 4 deals with determining the eligible options, whereas a probability is assigned to each of these branches in step 5. Step 6 represents the most important part of this reasoning process, as is now determined whether an instruction should be issued. In a final step, a branch is chosen by the agent (step 7).

The detailed behavior can be described as follows:

Step 1: Update Spatial Confidence

The spatial confidence ($conf$) updates at every intersection[2]. The amount in change is calculated according to equation 1 (as mentioned above, its co-domain is restricted to $[env\_sp\_ab \pm 0.2]$). If an agent received an instruction at the last intersection, the spatial confidence decreases, otherwise it increases. The rationale behind this mechanism is that wayfinders may perceive the fact that they received a route instruction as sign that they have taken wrong decisions in the past. This is, of course, intertwined with spatial abilities and, hence, agents with higher spatial abilities are less prone to loosing their spatial confidence.

$$conf\_corr\_term = 0.05 * (1 - env\_sp\_ab) + 0.01 \tag{1}$$

[2] The spatial confidence will not be updated for the first and the second intersection as no instruction is given at these junctions, see step 6.

Step 2: Calculate Cone Direction

The cone bisector is calculated according to the belief vector (*belief_vec*, see eq. 2). In line with prior evidence [18], the agent's orientation deteriorates with distance (the number of traversed junctions) but less so for agents with higher *env_sp_ab*. For each intersection, this belief vector is rotated away from the *true_dest_vec* by random choice. The rationale for this randomness is that there is no apriori knowledge about in which direction the erroneous *belief_vec* is rotated (see Figure 3).

$$belief\_vec = true\_dest\_vec \pm (1 - \frac{1}{\#traversed\_junctions}) * (1 - env\_sp\_ab) * 180° \quad (2)$$

Step 3: Calculate Cone Width

The width of the cone (*cone_width*) represents how confident an agent is regarding the direction to the destination. It is influenced (see eq. 3) by the agent's spatial confidence and the environmental complexity of the current junction (*env_comp*) whose impact is moderated by the agent's spatial abilities (the lower the environmental spatial abilities the higher the impact environmental complexity shows on the cone width). Before the whole simulation starts each junction in a city will be assigned a normally distributed environmental complexity (*env_comp*, $M = 0.5$, $SD = 0.2$) which will remain unchanged during all trials. A node for which $env\_comp = 0.5$ is, therefore, considered as decision point having an average environmental complexity. Based on the *cone_width* and the *belief_vec* the actual cone geometry is calculated (see Figure 3).

$$cone\_width = 360° - (conf * 360°) + (env\_comp - 0.5) * 360° * (1 - env\_sp\_ab) \quad (3)$$

Update Eligible Options (Step 4) and Calculate Probabilities for Eligible Options (Step 5)

In order to find the set of eligible branches, agents exclude any already visited dead end (memorized options) from the decision process (Step 4). Having done so, the cone is checked for eligible options and angles with respect to the *belief_vec* are calculated for each branch (Step 5). Three different cases are distinguished:

Option 1: No branch in cone All eligible options are taken into account and the angles between them and the *belief_vec* are calculated (least-angle strategy [20]).

Option 2: Exactly one branch in cone This branch is assigned a probability of 1.0.

Option 3: More than one branch in cone As in this case an agent can choose from several branches inside the cone, angles are found for these by analogy with option 1.

For options 1 and 3, these angles, denoted as *opt_ang*, need to be converted to probabilities using three further steps.

1. All angles are inverted with respect to the maximum angle within the cone which is given by $\frac{cone\_width}{2}$, thereby favoring angles which are closer to *belief_vec*: $inv\_angles = \frac{cone\_width}{2} - opt\_ang$. Subsequently, each inverted angle will be normalized (division by the sum of all inverted angles in the list) in order to ensure that the sum of all probabilities equals one.
2. In order to avoid back and forth movement along the same branch (see [19]), a factor called *already visited penalty factor* (*vis_pen*) is applied to the probability of any edge which has already been visited. The lower the value the higher the penalty. Again, the probabilities are normalized.

3. A final selection step for branches is needed as several branches may show almost the same angle to the bisector of the cone geometry, i.e., whose angles can hardly be distinguished by humans. Therefore, only those branches with a probability greater than $max\_probability - 0.1$ are selected and then the remaining probabilities are normalized.

The above procedure leads to the final set of branches FS with their final probabilities assigned. These will subsequently be used to decide if an agent needs an instruction or not.

Step 6: Determine Whether an Instruction is Given

Given the probabilities and several additional parameters a decision is made whether an instruction is given to the agent[3]. An instruction is provided for any of the following reasons, i.e., the list of reasons is checked one-by-one in the order given below:

1. The shortest path from the current junction to the destination leads over a single segment, i.e., the instruction is given in order to support destination recognition (see [9]).
2. Let *sp_length* denote the shortest path from the start to the destination; let further *dist_walked* denote the distance an agent has walked from the start to the current junction. Finally, let *max_dist* denote the constant factor which determines the allowed deviation from sp_length still rendering a trial successful. Then, the *current buffer* (*curr_buffer*), i.e., the distance an agent can walk from the current junction to the destination in order to still successfully finish a trial is given by equation 4.

$$curr\_buffer = max\_dist * sp\_length - dist\_walked \tag{4}$$

Let, furthermore, *buff_fact* (co-domain: $[0;1]$) denote a factor which is used to balance the number of given instructions against the number of agents that will arrive (given the presupposition that the probability of a successful trial increases for agents who receive more instructions). This means, this factor is used to account for the risk that the agent will exceed the available buffer: An instruction will be given if the current buffer multiplied by the buffer factor is lower than the length of the shortest path from the current junction (see eq. 5).

$$curr\_buffer * buff\_fact < sp\_length\_curr\_jct \tag{5}$$

3. For the same reason other branches are examined (step 2 is introduced in order to save computation time). We evaluate this case based on two steps. We, first, create the set of acceptable branches AB which includes all branches which fulfill inequality 7 in which *sp_over_i* denotes the sum of the length of the shortest path between the upcoming intersection i and the destination and the length of the edge from the current junction to i (see eq. 6).

$$sp\_over\_i = sp\_length_i + len(edge\_to\_i) \tag{6}$$

$$sp\_over\_i <= curr\_buffer * buff\_fact \tag{7}$$

Subsequently, we sum the probabilities of all branches $b \in AB$. If this sum is smaller than a predefined threshold called *pos_sum*, which is kept constant across trials, then an instruction is given.

[3] There is no instruction given at the first two nodes the agent traverses as it is reasonable to assume that the direction of the destination is still evident.

4. An instruction is, furthermore, given if an edge exists in the *final selection* FS (see step 5 above) for which the shortest path from the end node of this edge leads over the current node. Let the current junction be denoted as j_{i-1}; let the upcoming junction of a branch b_i which is part of the final selection set be denoted as j_i. An instruction will be given if the shortest path from j_i would lead over j_{i-1} because this will save agents a loss of *curr_buffer* due to avoidable detours.
5. Given the fact that the number of agents with a successful trial must be maximized, an instruction is also provided if agents have a high probability of choosing a branch which will be costly in terms of the consumed buffer while there would have been "cheaper" alternatives. Let *rem_len_buf* (Remaining Length Buffer, RLB) denote the difference (see eq. 8) between the *curr_buffer* and the *sp_over_i* (see eq. 6).

$$rem\_len\_buf = curr\_buffer - sp\_over\_i \tag{8}$$

Step 1: For all branches $b \in FS$ the ratio between the RLB of the branch with the highest probability and the RLBs of all other branches is checked. If this ratio is larger than a threshold *buff_diff*, this branch will be included in set BS, because it offers a better RLB. If $|BS| = 0$ no instruction is given.

Step 2: If $|BS| \geq 1$: Let $P(b_k)$ denote the probability assigned to the $k-th$ branch and $MAX(P(b_k))$ denote the highest probability of all branches in FS (note: FS is a superset of BS and the probabilities of branches in both sets are the same). For each branch in BS check whether inequality 9 holds in which *prob_diff* denotes a threshold for the ratio of the highest probability of all branches among FS and a given branch in BS.

$$\frac{MAX(P(b_k))}{P(b_k)} > prob\_diff \tag{9}$$

If this inequality holds, an instruction will be given, because chances are high that the agent misses a better RLB.

If none of these cases holds for the current junction, then no instruction is given and and the agent chooses an option (step 7) based on the probabilities (step 5) assigned to each branch. With those conditions we try to predict costly mistakes rather than correct them because some mistakes can be expensive and unrecoverable regarding the goal of reaching the destination within a given distance threshold.

Step 7: Choose an Option

At any junction agents either choose an option by following an instruction or by making a decision without having received an instruction. In the latter case, agents choose the branch they will continue on from the final selection set FS based on a weighted random choice. If an instruction was given, however, the same procedure as for the baseline applies (see above), although one important differences applies: The edge on which an agent traveled to the current junction is the only one which is excluded. Please note: Again, turn-around instructions are as well followed error-free.
This decision mechanism of giving an instruction remains the same for the whole route.

5 Results

In order to reduce the amount of combinations, a pre-test was done with 20 agents (out of 3000) and 15 routes (out of 100) using the following parameter values:

Maximum path length (*max_dist*)	$\{1.2, 1.35, 1.5\}$
Buffer factor (*buff_fact*)	$\{0.5, 0.6, 0.7, 0.8, 1.0\}$
Positive sum threshold (*pos_sum*)	$\{0.5, 0.75\}$
Buffer difference threshold (*buff_diff*)	$\{1.05, 1.2, 1.5\}$
Probability difference threshold (*prob_diff*)	$\{1.05, 1.2, 1.5\}$
Already visited penalty factor (*vis_pen*)	$\{0.1, 0.5, 0.75\}$

This yielded 810 different parameter combinations which were tried. Of those, for each city two parameter sets were chosen for the experiment, resulting in 6 different sets in total:

best_perc is the parameter set which yielded the maximum percentage of successful trials, thereby prioritizing the percentage of agents who arrive.

best_f_ch is the parameter set which represents a trade off (found by multiplication) between the percentage of successful trials and the number of given instructions.

Each of the six parameter sets was used for each city (3000 agents and 100 routes) resulting in 18 runs, overall. Of these, the two best performing runs for each city were selected for the final analysis (see Table 1) applying again the *best_perc* and *best_f_ch* criteria. There are, consequently, two datasets for every city for condition *free choice navigation*. Contrastingly, the baseline has only one dataset for each city as no additional parameters except *nav_instr* need to be set. An overview of the results is presented in Table 2. Generally speaking, more people arrive with the baseline condition across all cities. The parameter set for *best_f_ch* leads to a similar number of instructions per traversed node as for the baseline.

Table 1 The best parameter set for every city regarding *best_perc* (%) and *best_f_ch* (% * f_c). D – Djibouti, M – Mexico, V – Vienna.

City	Best at	max dist	buff fact	pos sum	buff diff	prob diff	vis pen
D	%	1.5	0.5	0.75	1.2	1.2	0.5
M, V	%	1.5	0.5	0.75	1.5	1.5	0.1
D, M, V	% * f_c	1.5	0.7	0.75	1.5	1.05	0.5

Next, we will present the analysis regarding our hypotheses. In order to analyse differences between both conditions bootstrapping ($B = 10000$ runs) was used and 95% percentile-based confidence intervals (CIs) are reported in square brackets. We refrain from calculating statistical tests due to the very large sample size. While there is a single dataset in the baseline condition, for our *free choice navigation* approach the relevant dataset (*best_perc* or *best_f_ch*) is chosen as appropriate.

In the following, we detail several hypotheses with respect to our approach and provide the results of our analysis.

Reduced Number of Navigation Instructions (H1) As described above (see Section 1), *free choice navigation* approach equips wayfinders with flexibility in terms of route choice. We, therefore, hypothesize that people who reach the destination within a distance of $1.5 \times sp\_len$ using our approach will receive less route instructions as compared to the baseline scenario.

Table 2 Comparison of baseline (B) and *free choice navigation* (FCN) for agents who arrived within a certain percentage (leftmost column) of the shortest path length being allowed to walk 150% of the shortest path. Parameter sets for condition *free choice navigation* are given in Table 1 (max_dist=1.5). *base*: dataset of baseline; *best_perc*/*best_f_ch*: datasets of *free choice navigation*; %: percentage of people who arrived; ipn: mean no. of instructions per traversed junction (ipn).

City	Djibouti						Mexico						Vienna					
Con.	B		FCN				B		FCN				B		FCN			
Dset	base		*best_perc*		*best_f_ch*		base		*best_perc*		*best_f_ch*		base		*best_perc*		*best_f_ch*	
Feat.	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn
110%	0.74	0.37	0.13	0.66	0.04	0.27	0.81	0.32	0.13	0.62	0.06	0.30	0.77	0.39	0.12	0.61	0.03	0.20
120%	0.9	0.39	0.30	0.68	0.11	0.28	0.95	0.33	0.32	0.66	0.16	0.31	0.92	0.4	0.34	0.64	0.12	0.24
130%	0.96	0.39	0.51	0.7	0.24	0.31	0.98	0.33	0.55	0.69	0.30	0.33	0.97	0.40	0.59	0.67	0.25	0.28
140%	0.98	0.4	0.76	0.72	0.45	0.36	0.99	0.33	0.78	0.72	0.52	0.37	0.99	0.41	0.83	0.69	0.48	0.34
150%	0.99	0.4	0.91	0.74	0.81	0.43	1.0	0.33	0.9	0.74	0.81	0.43	1.0	0.41	0.95	0.71	0.85	0.41

Our figures do not support this hypothesis: For all cases, the mean difference in instructions given per traversed junction[4] between the baseline and our approach (*best_f_ch*) is negative, i.e., less instructions were given in the baseline condition: For Djibouti ($M = -0.037$, $SD = 0.0004$,[-0.0379; -0.0361]) our approach yielded on average one additional instruction every 27 ($\frac{1}{mean}$) junctions, whereas in Mexico ($M = -0.103$, $SD = 0.0004$, [-0.104; -0.102]) this value increases to every 10 junctions. The smallest difference between the two conditions was found for Vienna ($M = -0.004$, $SD = 0.0004$, [-0.005; -0.003]) where one additional instruction every 250 junctions is expected.

Longer Routes Enable More Free Choices (H2) Based on the fact that longer routes result in an increased maximum absolute route length and in line with H1, we also assume that successful agents will have made a higher number of free choices on longer routes. Similar to H1, our results (*best_f_ch*) do not support this hypothesis. We found a weak negative Spearman correlation between the number of junctions traversed and the % of free choices of all decisions an agent made across cities. Djibouti ($M = -0.168$, $SD = 0.002$, [-0.172; -0.164]) and Vienna ($M = -0.179$, $SD = 0.002$, [-0.183; -0.175]) showed a stronger correlation than Mexico ($M = -0.119$, $SD = 0.002$, [-0.123; -0.116]).

Percentage of People Reaching Destination (H3) The *free choice navigation* we suggest imposes increased cognitive load on wayfinders: They have to make spatial decisions based on path integration and their belief about the destination vector (see Section 2). Therefore, we hypothesize that, within a given maximum distance threshold (150%), more people will arrive at the destination with the baseline than with our *free choice navigation* approach.

Our data is in line with this assumption. Again, the difference between the baseline and *free choice navigation* (*best_perc*) is reported: In Djibouti ($M = 0.085$, $SD = 0.0005$, [0.084; 0.086]) on average 8.5 percentage points less trials ended successfully. In Mexico ($M = 0.100$, $SD = 0.0005$, [0.099; 0.102]) the figures show 10 percentage points. For Vienna ($M = 0.047$, $SD = 0.0004$, [0.046; 0.048]), again, the smallest difference compared to the baseline was found, showing an average difference of 4.7 percentage points.

Low Spatial Abilities of Failures (H4) Based on the need to make their own spatial decisions (see also H2), we assume that the fraction of people, who is not able to arrive at the destination within a threshold of $1.5 \times sp\_length$, will be highest within those agents who show low spatial abilities.

[4] The number of obtained instructions was normalized by the number of traversed nodes as *free choice navigation* agents walked on average more.

Table 3 Numbers regarding failed trials: a) Share of failed trials per city and ability category. b) Share of agents who failed at least once.

(a) The share of failed trials within a 150% distance threshold categorized by city and env. spatial abilities.

City	Low	Medium	High
Djibouti	25.95	6.95	1.34
Mexico	28.99	7.68	0.79
Vienna	16.47	3.46	0.23

(b) Share, mean (M) and standard deviation (SD) of agents for a given category of env. spatial abilities **who failed one or more trials**. *low* (521): $[0; 0.3]$; *medium* (2028): $(0.3; 0.7]$; *high* (451): $[0.7; 1]$

City	Low			Medium			High		
Feat.	%	M	SD	%	M	SD	%	M	SD
D	100%	.2	.079	99%	.50	.11	79%	.79	.07
M	100%	.2	.079	98%	.50	.11	51%	.77	.06
V	100%	.2	.079	86%	.49	.10	20%	.75	.05

In order to investigate this hypothesis, agents are categorized, based on their *env_sp_ab* and its standard deviation, into 3 groups: low ([0;0.3], $N_{low} = 521$), medium ((0.3;0.7], $N_{med} = 2028$) and high ((0.7;1], $N_{high} = 451$). The data obtained by the simulation (*best_perc*) supports our assumption: Across cities (*best_perc*) agents with *low env_sp_ab* show the highest share of failed trials (see Table 3a). Moreover, each agent with low spatial abilities failed at least on one trial (see Table 3b). In Vienna 20% of high-level agents did not reach their destination *at least once*, whereas in Djibouti and Mexico this share was 79% and 51%, respectively.

Higher Spatial Abilities Yield Shorter Routes (H5) Based on prior evidence on path integration (see e.g., [24]) we assume that wayfinders with high spatial abilities will be able to take shorter routes, in terms of deviation from shortest path length.

There is a strong negative correlation between *env_sp_ab* and the path length (*best_perc*); which supports this hypothesis. Both, Djibouti ($M = -0.50$, $SD = 0.002$, [-0.504; -0.498]) and Mexico ($M = -0.507$, $SD = 0.002$, :[-0.51; -0.504]) show similar correlations, whereas Vienna ($M = -0.566$, $SD = 0.001$, [-0.568; -0.563]) shows a stronger correlation.

6 Discussion and Limitations

We will discuss the results of our agent-based simulation along two lines. First, we will discuss our findings and contributions with respect to the idea of *free choice navigation*. Second, we will continue with respect to the plausibility of the model and its limitations.

6.1 Discussion

Using TBT navigation systems, users are required to follow a predefined route including predefined turns. This system behavior, however, results in a reduced interaction between users and the spatial environment, ultimately leading to (potentially) adverse effects in terms of spatial orientation. The primary goal of this paper is, therefore, to propose the concept of *free choice navigation* and initially test this assistance approach by means of a simulation study. Our approach has the potential to remedy these effects and is expected to foster spatial knowledge acquisition as it aims to give user more freedom and, at the same time, ensures reasonable route lengths.

Generally speaking, plausibility and validity are both important concepts in simulation studies [5]. While the former can be be judged according to specific figures, the latter requires empirical evidence. Checking validity must, hence, be left for future work (see Section 7); our figures, however, indicate the plausibility of agent behavior. Our *free choice navigation* approach is plausible as cities with different morphologies [32] yield different results (see Tab. 2) which is also in line with prior evidence (see e.g., [4]). This difference is also reflected in our results regarding H1: Our approach does not yield less navigation instructions per traversed node compared to the baseline system. While the effect can be neglected for Vienna (average route length: 87.8 junctions, i.e., 0-1 instructions more than the baseline system) and is of low relevance for Djibouti (mean length: 67.5 junctions, i.e,. 2-3 instructions more), a considerable increase (mean length: 70.6 junctions, i.e., 7 instructions more) can be seen for Mexico City, where 10% more instructions are needed than in the baseline condition. The reasons as well as the impact on user experience leaves much room for further research.

The plausibility of our model is further supported by our results regarding H3, H4, H5: Less people arrived with our approach than in the baseline condition (H3), agents with low environmental spatial abilities fail more often (H4) and the higher these abilities the shorter the path taken (H5). In addition to that, each agent which has low abilities does not reach its destination at least once (see Table 3b). All of these results are in line with our expectations and, taken together, suggest that environmental spatial abilities play a key role (see future work below). Having said this, the simulation results for our *free choice navigation* approach yield, moreover, promising results with respect to success rate (i.e., reaching the destination within $1.5 \times len(shortest\_path)$) and distance traveled: In each city more than 90% of all agents arrive within this threshold. More importantly, on average this upper limit was not reached at all (Djibouti: $M = 1.26$, $SD = 0.13$; Mexico: $M = 1.25, SD = 0.127$; Vienna: $M = 1.25$, $SD = 0.121$). A mean detour of about 25% seems reasonable in a leisure scenario and our approach yields shorter average distances than reported in other, vibro-tactile based, beeline studies (see e.g., [29] in which mean distances greater than $1.5 \times len(shortest\_path)$ are reported). While the number of route instructions issued is not less than for the baseline system the *free choice navigation* approach proposed allows for a particularly high share of free choices (Djibouti: 0.57, Mexico: 0.57, Vienna: 0.59) which results in a lot of engagement with the spatial environment traversed. Having said this, however, our results do not support hypothesis H2: We found a weak negative correlation between the number of traversed intersections and the share of free choices along a route (i.e., the number of intersections at which no route instruction is given): One possible reason for that can be that the parameter set produces an artifact in the data, hence, further research is needed. Furthermore, the higher overall success rate and the lower share of agents with medium and high environmental spatial abilities which did not arrive at least once (see Table 3b) suggest Vienna to be easier to navigate than Djibouti and Mexico City.

Taken together, this discussion reveals that the *free choice navigation* is reasonable. At the same time, the chosen parameters are crucial for the figures achieved. Clearly, our model is not optimal and can, therefore, act as a baseline other researchers can compete with. There are several possibilities for improvement: For example, reducing the number of instructions or increasing the percentage of arrived agents. As a consequence, the data will be published at `https://geoinfo.geo.tuwien.ac.at/resources/`

6.2 Limitations

Despite the promising results, several limitations apply. On the one hand, the environment can be modeled more complex considering for example junction geometry [11] or environmental data like building footprints or points of interests. On the other hand, a more elaborate modeling of agents is feasible, in particular with respect to interpretation of route instructions (of different types) [34] or by considering further wayfinding preferences [3]. A further limitation of our work is related to the application of the introduced cone (see Section 2) for real scenarios. We assumed to know the approximate direction that agents would follow (i.e., the direction of the cone). To apply this to humans, it is necessary to know the direction they will follow. Recent research in human activity recognition has shown very positive results (e.g., [38, 2]), which can be used for our purpose to determine the direction of the cone.

7 Conclusion and Future Work

We introduced *free choice navigation*, a novel approach with the intention to increase the freedom of choice during navigation. This approach was evaluated by means of an agent-based simulation study and compared against a TBT approach, serving as a baseline. The agent-based model used for the simulations is a further contribution, introducing the concept of the *cone*, which encodes the user's spatial abilities and confidence. Our findings are in line with our expectations concerning the proportion of free choices during navigation as well as the impact of spatial abilities on the effectiveness of our approach. Furthermore, the results confirm the plausibility of the introduced agent-based model.

Future human subject experiments in real-world environments are required in order to address a series of open research questions. First, the validity of the presented agent-based model could be investigated by comparing the simulated results with the ones obtained from humans in a real environment. Furthermore, we expect that the *free choice navigation* will foster spatial knowledge acquisition due to the increased engagement with the environment. Along the same line, also aspects concerning user experience, cognitive load, or uncertainty should be addressed in human subject experiments. The data and model will be made available and can serve as a baseline for further development. The model and the results can, thus, be used by the community as a benchmark for future iterations of the model.

References

1 S. Abar, G. K. Theodoropoulos, P. Lemarinier, and G. O'Hare. Agent based modelling and simulation tools: A review of the state-of-art software. *Comp. Science Review*, 24:13–33, 2017.

2 N. Alinaghi, M. Kattenbeck, A. Golab, and I. Giannopoulos. Will You Take this Turn? Gaze-Based Turning Activity Recognition During Navigation. In K.Janowicz and J. A. Verstegen, editors, *11th Int. Conf. on Geographic Information Science (GIScience 2021) - Part II*, 2021.

3 J. N. Bailenson, M. S. Shum, and D. H. Uttal. Road climbing: Principles governing asymmetric route choices on maps. *J. of Env. Psychology*, 18(3):251–264, 1998.

4 D. Bhowmick, S. Winter, and M. Stevenxon. Comparing the costs of pedestrian wayfinding heuristics across different urban network morphologies. *GeoComputation*, pages 1–15, 2019.

5 L. Crociani, G. Vizzari, D. Yanagisawa, K. Nishinari, and S. Bandini. Route choice in pedestrian simulation: Design and evaluation of a model based on empirical observations. *Intelligenza Artificiale*, 10(2):163–182, 2016.

6 L. Dahmani and V. D. Bohbot. Habitual use of GPS negatively impacts spatial memory during self-guided navigation. *Scientific Reports*, 10(1):1–14, 2020.

7 N. Dethlefs, Y. Wu, A. Kazerani, and S. Winter. Generation of adaptive route descriptions in urban environments. *SPAT COGN COMPUT*, 11(2):153–177, 2011.

8 D. Dobbelstein, E. Rukzio, and P. Henzler. Unconstrained pedestrian navigation based on vibro-tactile feedback around the wristband of a smartwatch. *Proc. of CHI '16, p.2439–2445*, 2016.

9 R.M. Downs and D. Stea. *Maps in Minds: Reflections on Cognitive Mapping*. Geography Series. Harper & Row, 1977.

10 G. Filomena, E. Manley, and J. A. Verstegen. Perception of urban subdivisions in pedestrian movement simulation. *PLoS ONE*, 15(12):1–27, 2020.

11 P. Fogliaroni, D. Bucher, N. Jankovic, and I. Giannopoulos. Intersections of Our World. In Winter et al., editor, *10th Int. Conf. on Geographic Information Science*, 2018.

12 D. Gallo, S. Shreepriya, and J. Willamowski. RunAhead: Exploring Head Scanning based Navigation for Runners. In *Proc. of CHI 2020.*, pages 1–13, 2020.

13 A. Gardony, T. Brunyé, and H. Taylor. Navigational Aids and Spatial Memory Impairment: The Role of Divided Attention. *SPAT COGN COMPUT*, 15(4):246–284, 2015.

14 I. Giannopoulos, P. Kiefer, and M. Raubal. Gazenav: Gaze-based pedestrian navigation. In *Proc. of MobileHCI 2015*, page 337–346. ACM, 2015.

15 I. Giannopoulos, P. Kiefer, M. Raubal, K. F. Richter, and T. Thrash. Wayfinding decision situations: A conceptual model and evaluation. In *Int. Conf. on Geographic Information Science*, pages 221–234. Springer, 2014.

16 K. Gramann, P. Hoepner, and K. Karrer-Gauss. Modified navigation instructions for spatial navigation assistance systems lead to incidental spatial learning. *FRONT PSYCHOL*, 8, 2017.

17 A. A. Hagberg, D. A. Schult, and P. J. Swart. Exploring network structure, dynamics, and function using networkx. In G. Varoquaux, T. Vaught, and J. Millman, editors, *Proc. of the 7th Python in Science Conf.*, pages 11–15, Pasadena, CA USA, 2008.

18 S. K. Harootonian, R. C. Wilson, L. Hejtmánek, E. M. Ziskin, and A. D. Ekstrom. Path integration in large-scale space and with novel geometries: Comparing vector addition and encoding-error models. *PLoS computational biology*, 16(5):e1007489, 2020.

19 H. Hochmair. Investigating the effectiveness of the least-angle strategy for wayfinding in unknown street networks. *Env and Planning B: Planning and Design*, 32(5):673–691, 2005.

20 H. Hochmair and A. Frank. Influence of estimation errors on wayfinding-decisions in unknown street networks – analyzing the least-angle strategy. *SCC*, 2(4):283–313, 2002.

21 T. Ishikawa. Satellite Navigation and Geospatial Awareness: Long-Term Effects of Using Navigation Tools on Wayfinding and Spatial Orientation. *Prof. Geographer*, 71(2), 2019.

22 D. Jonietz and P. Kiefer. Uncertainty in Wayfinding: A Conceptual Framework and Agent-Based Model. In E. Clementini et al., editor, *Proc. of COSIT 2017*, pages 15:1–15:14, 2017.

23 Angelika Kneidl. *Methoden zur Abbildung menschlichen Navigationsverhaltens bei der Modellierung von Fußgängerströmen*. Dissertation, Technische Universität München, 2013.

24 J. M. Loomis, R. L. Klatzky, R. G. Golledge, and J. W. Philbeck. Human navigation by path integration. In *Wayfinding Behavior*, pages 125–151. Johns Hopkins University Press, 1999.

25 C. Magnusson, K. Rassmus-Gröhn, and D. Szymczak. Navigation by pointing to GPS locations. *Personal and Ubiquitous Computing*, 16(8):959–971, 2012.

26 M. Pielot and S. Boll. Tactile wayfinder: Comparison of tactile waypoint navigation with commercial pedestrian navigation systems. In P. Floréen, A. Krüger, and M. Spasojevic, editors, *Proc. of the 8th Int. Conf. on Pervasive Computing*, pages 76–93. Springer Berlin Heidelberg, 2010.

27 A. Rao and M. Georgeff. BDI Agents: From Theory to Practice. *Proc. of ICMAS '95*, pages 312–319, 1995.

28 K. F. Richter and M. Duckham. Simplest instructions: Finding easy-to-describe routes for navigation. In T. J. Cova, H. J. Miller, K. Beard, A. U. Frank, and M. F. Goodchild, editors, *Geographic Information Science*, pages 274–289, Berlin, Heidelberg, 2008. Springer.

29 S. Robinson, M. Jones, P. Eslambolchilar, R. Murray-Smith, and M. Lindborg. "I Did It My Way": Moving Away from the Tyranny of Turn-by-Turn Pedestrian Navigation. In *Proc. of MobileHCI '10*, pages 341–344, 2010.

30 G.-L. Savino, L. Meyer, E. Schade, T. Tenbrink, and J. Schöning. Point me in the right direction: Understanding user behaviour with as-the-crow-flies navigation. In *Proc. of MobileHCI '20*, pages 1–11, 2020.

31 F. Shatu, T. Yigitcanlar, and J. Bunker. Shortest path distance vs. least directional change: Empirical testing of space syntax and geographic theories concerning pedestrian route choice behaviour. *J. of Transport Geography*, 74(May 2018):37–52, 2019.

32 J. Thompson, M. Stevenson, and J. S. Wijnands et al. (8). A global analysis of urban design types and road transport injury: an image processing study. *The Lancet Planetary Health*, 4(1):e32–e42, 2020.

33 P. W. Thorndyke and B. Hayes-Roth. Differences in spatial knowledge acquired from maps and navigation. *Cognitive psychology*, 14(4):560–589, 1982.

34 L. B. Tschander, H. R. Schmidtke, C. Eschenbach, C. Habel, and L. Kulik. A geometric agent following route instructions. In *Int. Conf. on Spatial Cognition*, pages 89–111. Springer, 2002.

35 J. M. Usher and L. Strawderman. Simulating operational behaviors of pedestrian navigation. *Computers & Industrial Engineering*, 59(4):736–747, 2010.
36 A. Wunderlich and K. Gramann. Electrocortical evidence for long-term incidental spatial learning through modified navigation instructions. In *Proc. of Spatial Cognition '18*, 2018.
37 D. Xu, X. Huang, J. Mango, X. Li, and Z. Li. Simulating multi-exit evacuation using deep reinforcement learning. *Transactions in GIS*, pages 1–23, 2021.
38 J. Ye, X. Li, X. Zhang, Q. Zhang, and W. Chen. Deep learning-based human activity real-time recognition for pedestrian navigation. *Sensors*, 20(9), 2020.
39 H. D. Zimmer, S. Münzer, and J. Baus. *From Resource-Adaptive Navigation Assistance to Augmented Cognition*, pages 35–53. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010.