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Journal of Environmental Psychology 24 (2004) 475–493

Journal of ENVIRONMENTAL PSYCHOLOGY

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Use and interaction of navigation strategies in regionalized environments

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Abstract

In this work, three experiments are reported that studied the use and interaction of navigation strategies both during the learning of a virtual environment and during subsequent route planning tasks. Special interest concerned the role of regions within the environments. Results from Experiment 1 suggest that the regions are perceived and encoded in spatial memory very early during the process of learning an environment. During navigation such regional information could be used to overcome missing or imprecise spatial information on the detailed level. Experiments 2 and 3 studied the use and interaction of route planning strategies that are applied after an environment has been learned. Results suggest (i) that human route planning takes into account region-connectivity and is not based on place-connectivity alone, (ii) that route planning takes into account the distribution of multiple target locations and (iii) that route planning takes into account the complexity of alternative paths.

1. Introduction

"Traditionally, the path selection problem has been ignored or assumed to be the result of minimizing procedures such as selecting the shortest path, the quickest path or the least costly path." This statement by Golledge (1995) is still true today. Very little work has been attributed to the question which mechanisms, strategies and heuristics are applied during route planning that allow to derive the shortest path, the quickest path or the least costly path from spatial memory. In this work three navigation experiments in virtual environments are reported that studied the use and the interaction of different navigation strategies that are applied during the exploration and learning of an environment and during subsequent route planning tasks.

Wayfinding and navigation behavior have been mainly used as a tool to study the underlying representation of space. Aginsky, Harris, Rensink, and Beusmans (1997), e.g. monitored subjects spatial knowledge of a virtual environment during the learning of a route through that environment. They found that only relevant spatial information, i.e. information in the vicinity of choice points, was retained. In navigation experiments in virtual reality, Gillner and Mallot (1998) showed that subjects store local elements (i.e. places or views associated with movement instructions and expected outcomes) in spatial memory. These local elements did not have to be globally consistent, suggesting that representations of space are graph-like structures rather than map-like structures (see Schölkopf & Mallot, 1995). Supporting evidence for graph-like representations of space also comes from navigation experiments in virtual environments, containing both global and local landmark information (Steck & Mallot, 2000). Global landmarks were distant landmarks such as towers and mountains that were visible from a large area, thus providing a global reference frame. Local landmarks, on the other hand, were objects at decision points and were visible only from a small distance. After learning the virtual environment, the global and local

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doi:10.1016/j.jenvp.2004.09.006

landmark information was set in conflict by rotating the global landmarks while keeping local landmarks stable. Surprisingly, subjects did not perceive nor report this conflict. Moreover, subjects who relied on global landmark information in the conflict situation showed good wayfinding performance if only local landmark information was provided and vice versa. Geographical slant has been shown to improve navigation and wayfinding performance as well as directional judgments in a virtual environment setup, suggesting that slant or height information is integrated in spatial memory (Steck, Mochnatzki, & Mallot, 2003; Restat, Steck, Mochnatzki, & Mallot, 2004).

Navigation and wayfinding procedures have also been used to evaluate the navigability of architectural spaces. O'Neill (1992) demonstrated that wayfinding performance decreased with increasing plan complexity (for measures of floor plan complexity see O'Neill, 1991; Raubal & Egenhofer, 1998). Furthermore, Werner and Long (2003) have shown that the misalignment of local reference systems impairs the user's ability to integrate spatial information across multiple places, suggesting that reference axes should be consistent throughout a building in order to support navigability. Janzen, Herrmann, Katz, and Schweizer (2000) investigated the influence of oblique angled intersections within an environment on wayfinding performance. When navigating arrow-fork intersections, subjects error rate depended on which branch they entered the intersection (see also Janzen, Schade, Katz, & Herrmann, 2001).

Numerous navigation experiments studied gender differences in spatial cognition, which are supposed to be one of the most reliable of all cognitive gender differences in humans (Moffat, Hampson, & Hatzipentalis, 1998). Astur, Ortiz, and Sutherland (1998), e.g. have developed a virtual version of the Morris water maze task for humans. Subjects were placed in a virtual pool that was surrounded by distal cues and were instructed to escape from the water as quickly as possible by navigating towards a hidden platform. Results revealed a gender effect: males swam for shorter time to find the platform, and after removing the platform males spent more time in the quadrant where the platform has previously been. While this study suggested a gender difference favoring males in spatial performance, other studies have reported the use of different aspects of the environment (e.g. global and local landmarks) and the use of different orientation and navigation strategies between subjects (e.g. Lawton, 1994, 1996; Sandstrom, Kaufman, & Huettel, 1998; Lawton & Kallai, 2002), rather than fundamental performance differences. Basically, these studies state that male subjects rely more on global landmark configurations or global reference systems, while female subjects tend to rely on local landmark information and route information. In a neuroimaging study, Grön, Wunderlich, Spitzer, Tomczak, and Riepe (2000) have reported gender differences in brain activation as subjects searched their way out of a virtual maze. While there was as great overlap of brain area activation between genders, including the right hippocampus, Grön et al. report specific activation of the left hippocampus in males, and specific activation of right parietal and right prefrontal cortex for females.

Only few navigation experiments aimed at understanding the mechanisms and strategies that underlie route planning and navigation behavior. Gärling and Gärling (1988), e.g. investigated pedestrian shopping behavior with respect to distance minimization in multistop shopping routes. Most shoppers that minimized the distance of their shopping routes, first chose the location farthest away, most probably to minimize effort to carry bought goods, and then minimized distances locally between shopping locations (see also Gärling, Säisä, Böök, & Lindberg, 1986). This so called locally minimizing-distance (LMD) heuristics, also often referred to as the nearest neighbor (NN) heuristic in artificial intelligence approaches (e.g. Golden, Bodin, Doyle, & Stewart, 1980), is known to generally lead to optimal or near optimal solutions in traveling salesman problems of small sizes.

Insights into navigation strategies also come from the animal literature. For example, Gallistel and Cramer (1996) studied vervet monkeys' ability to navigate the shortest route connecting multiple locations, by arranging baited locations in a group of four to one side and a group of two to the other side (see Fig. 1a). Note that the nearest baited location of both food patches were equidistant from the starting point. An algorithm like the NN predicts that monkeys choose to first visit both of the food patches equally often. However, the vervet monkeys first visited the richer food patch in all trials. Below we refer to this strategy as the *cluster*-strategy. In a second experiment Gallistel and Cramer (1996) arranged baited locations in a diamond shape. If the monkeys intended to return to the starting position, because it was baited after the monkey left it, the

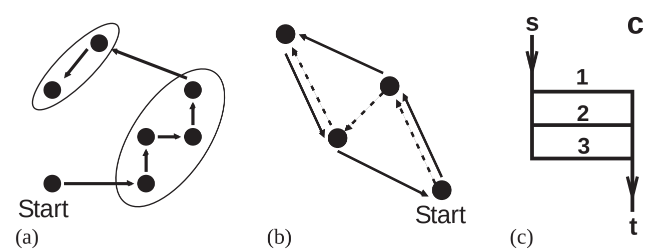


Fig. 1. (a) The unequal sides test by Gallistel and Cramer with a large and a small food patch. (b) The dashed route is optimal, when the starting position was not re-baited, the solid route is optimal if the starting position was re-baited. (c) Navigating from start (*s*) to target (*t*), subjects preferred the last route number 3 above the alternative routes with equal metric length.

monkeys generally chose the shortest route in this traveling salesman task (see solid route in Fig. 1b). Here an NN strategy would predict that the monkeys followed a different nonoptimal route (see dashed route in Fig. 1b) for the first steps. Gallistel and Cramer (1996) concluded that the vervet monkeys' route planning not only takes the first step into account (as predicted by the NN), but is indeed planning three steps ahead (see also Menzel, 1973).

Christenfeld (1995) studied human subjects' preference to choose a certain route from a series of almost identical routes. In all conditions (route choice from artificial maps, from street maps or in real-world environments) subjects had the choice between a number of routes that were identical with respect to metric length, target point and the number of turns. The only difference between the routes was when along the route subjects had to make a turn. In all conditions, subjects delayed the turning decision as long as possible (see Fig. 1c). Christenfeld speculated that this effect resulted from subjects tendency to minimize mental effort, that is to say, subjects did not worry about where to turn until they had to turn. This strategy offers a possible explanation for the fact that people's route choices are often asymmetric; i.e. subjects choose different routes from A to B than from B to A (e.g. Stern & Leiser, 1988). On the basis of results from route planning from maps, Bailenson, Shum, and Uttal (1998, 2000) extended Christenfeld's findings and suggested that subjects, when choosing between alternative routes from maps, prefer routes with the longest initial straight segment (Initial segment strategy—ISS), in order to leave the starting region as fast as possible (Route climbing principle).

In this work, route planning is defined as the process of selecting and navigating a path from a given starting location to a single or to multiple target locations that are beyond the sensory horizon of the agent. The spatial information needed to plan the route therefore has to be retrieved from spatial memory.

Human spatial memory has a certain property, namely its hierarchical organization that lately has been shown to influence route planning and navigation behavior (Wiener & Mallot, 2003). Hierarchical theories of spatial representations state that spatial memory contains nested levels of detail. Such a memory structure can be expressed in graph like representations of space in which locations are grouped together and form superordinate nodes. For example, places are grouped together and form regions. Spatial relations among regions can then be represented at the region level. Supporting evidence for the hierarchical theories came from distance- and directional-judgments, spatial priming, and memory recall procedures. Stevens and Coupe (1978), e.g. have shown that directional judgments between locations are distorted towards the spatial relations of the states they reside in. Wilton (1979) has shown faster directional judgments between locations that reside in different regions, as compared to locations that reside in the same region. In a speeded recognition task McNamara (1986) revealed stronger priming, that is faster recognition times, when prime and target were objects from the same region of a previously learned layout than when prime and target were objects from different region of the same layout (see also McNamara, Ratcliff, & McKoon, 1984; McNamara & LeSueur, 1989; McNamara, Hardy, & Hirtle, 1989). Hirtle and Jonides (1985) have shown that subjects underestimated relative distances between landmarks from the same subjective region, while they overestimated absolute distances between landmarks from different subjective regions. Among others, these results have led to the hierarchical theories of spatial representations.

Wiener and Mallot (2003) studied the influence of regions within an environment on human route planning behavior. In a virtual reality setup subjects learned environments that were divided into different regions by active navigation. After learning the environments subjects were asked to either find the shortest route to a single target-place or to find the shortest route for visiting three places within the environment. Subjects minimized the number of region boundaries they crossed during navigation and subjects preferred paths that allowed for fastest access to the region containing the target. These findings suggest that human route planning takes into account region-connectivity and is not based on place-connectivity alone. Wiener and Mallot proposed the *fine-to-coarse* planning heuristic, a cognitive model that describes this simultaneous use of spatial information at different levels of detail during route planning. The core of this *fine-to-coarse* heuristic is the 'focal representation' that is generated from the hierarchical reference memory of space by using fine space information (place-connectivity) exclusively for the current location and the close surrounding and coarse space information (regions-connectivity) exclusively for distant locations. In this focal representation, the shortest path to the next target (target-place or target-region) is planned. Planning a route in such a *focal* representation results in a detailed plan for the close surrounding, allowing for immediate movement decisions, while only coarse spatial information is available for distant locations. The route plan therefore has to be refined during navigation. By updating the focal representation and by re-planning the route, a detailed plan for the next movement decisions is available at all times along the route. By using spatial information at different levels of detail for close and distant location not only memory load is reduced, but also the complexity of the planning task itself. Additionally memory load for the route plan is minimized, since steps are planned only one at a time.

Other route planning schemes that make use of hierarchical representations of space have been suggested in computational models of spatial cognition. Chown, Kaplan, and Kortenkamp (1995), e.g. suggested that higher abstraction levels of the representation are used to first generate coarse route plans. Such plans are simple, easy to compute, and rule out a large number of suboptimal paths. However, in order to allow for actual movement decision at choice points these plans have to be broken down and fine route plans have to be generated. Usually, such planning schemes, in which first a coarse route plan is generated that is then successively refined, are referred to as *coarse-to-fine* planning schemes.

This work aims at further investigating mechanisms and strategies that underlie human route planning by the means of navigation experiments in virtual environments. In the first part of this work one experiment is presented that studied the formation of hierarchical components, i.e. regional information, in human spatial memory. It will be argued that regional information is formed early during the cognitive mapping process and that this information is used in simple search tasks. In the second part, two experiments are presented that studied navigation- and route planning-strategies employed after learning a regionalized environment. The focus of this part concerns the use and interaction of three navigation strategies: (i) it will be tested whether the *cluster*-strategy (explained above, Gallistel & Cramer, 1996) is also used by human navigators, (ii) the use of the *fine-to-coarse* planning heuristic is further investigated (Wiener & Mallot, 2003), (iii) the influence of the complexity of alternative paths on human route planning and navigation behavior is studied. It is proposed that human navigators plan their routes in order to minimize the complexity of the planned path; this strategy is referred to as the *least-decision-load* strategy. It will be argued that all three navigation strategies are applied by human navigators, and that subjects' path choice behavior in these experiments can be predicted by a simple linear combination of the three navigation strategies.

2. General material and methods

All experiments presented in this work were conducted using virtual reality technology. Subjects actively navigated through virtual environments in the ego perspective and executed a series of navigation tasks. The use of virtual reality technology for navigation experiments has two major advantages as compared to real world experiments. First, it allows for exact control of the visual stimuli presented and second, one can carry out the experiments in environments created to exactly match the experimental demands.

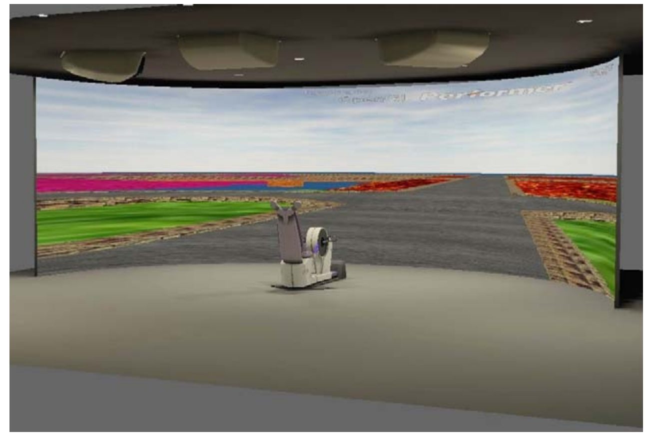


Fig. 2. Experimental setup with the 180° projection screen and the bicycle trainer.

2.1. The experimental setup

Experiments were conducted in the Virtual Environments Laboratory of the Max Planck Institute for Biological Cybernetics. For all experiments we created a particular virtual environment using the software Multigen Creator (MultiGenParadigm). A detailed description of the virtual environments is given in the 'Methods' sections of each experiment (see Sections 3.2.1, 4.2.1 and 5.2.1).

The visual scenery was rendered on a three-pipe Silicon Graphics Onyx2 InfiniteReality II (Silicon Graphics Inc., Mountain View, CA), running a C++ Performer simulation software that we designed and programmed. The scenery was then projected by means of three CRT projectors (Electrohome Marquee 8000; Electrohome Limited, Kitchener, Ontario, Canada) on a large half-cylindrical screen (7 m diameter and 3.15 m height) with a rate of 36 frames per second and an overall resolution of approximately 3500×1000 pixels.

Subjects were seated in front of this screen (see Fig. 2) either at a table or on a bicycle trainer. The experimental setup allowed for a 180° horizontal and a 50° vertical field of view. The simulation software guided subjects through the experiments, presented pictures of the navigation goals on the projection screen, and recorded the data. A detailed description of the setup can be found in van Veen, Distler, Braun, and Bülthoff (1998).

3. Formation of hierarchies in spatial memory (Experiment 1)

3.1. Purpose

As stated in the introduction, there is convincing evidence that human spatial memory is hierarchically structured. Here a navigation experiment is reported that studied the perception and encoding of environmental regions, i.e. the formation of hierarchical components in spatial memory, during the learning of an environment. The experiment was motivated by the assumption that regional knowledge that arose early during the process of learning an environment, provided additional information about the environment that could be used to facilitate learning and to compensate for missing or imprecise spatial knowledge at the detailed level. For example, the search for specific locations could be restricted to the appropriate regions. By executing search tasks, subjects either learned a virtual environment that was divided into different regions or a virtual environment that did not contain predefined regions. Subjects' navigation behavior in the regionalized and in the unregionalized environment was monitored and compared in order to study the perception, encoding and use of regional information.

3.2. Method

3.2.1. The virtual environment

An open space virtual environment was created that contained 16 showcases in its center. The showcases were arranged on a 4×4 squared grid with a mesh size of 100 m (see Fig. 3). Each showcase was placed on a circular ground plate with a radius of 7.5 m. If subjects entered the ground plate a single object within the showcase became visible. The objects are therefore referred to as pop-up landmarks, the corresponding ground plates are referred to as the landmarks' catchment areas. While its associated landmark uniquely specified each showcase, the landmarks were grouped into four different semantic groups according to the object category (4 cars, 4 animals, 4 buildings, 4 flowers).

Two versions of the virtual environment were created that only differed in the arrangement of the objects within the showcases. While objects from the same object category were neighboring each other in the regionalized environment, the objects were pseudo randomly distributed about the 16 positions in the unregionalized environment. Fig. 4 demonstrates the arrangement of the objects within the environment for both of the experimental environments. Four global landmarks were placed in the far distance of the environment to make sure that subjects could always localize themselves (see Fig. 3). By averaging all distances from all places to all other places carrying objects from the same category, a distance measurement was obtained that described the order of the environment. Mean order for the regionalized environment was 113.8 m; mean order for the unregionalized environment was 247.5 m.

3.2.2. Procedure

Subjects were randomly assigned to one of two experimental conditions. Subjects from the 'regionalized' condition conducted the experiment in the regionalized environment, while subjects from the 'unregionalized' condition conducted the experiment in the unregionalized environment. Subjects were seated on a bicycle trainer and could freely move through the environment by pedaling (translation) and tilting (rotation) the bicycle. They were repeatedly asked to search for showcases containing a specific object. The target

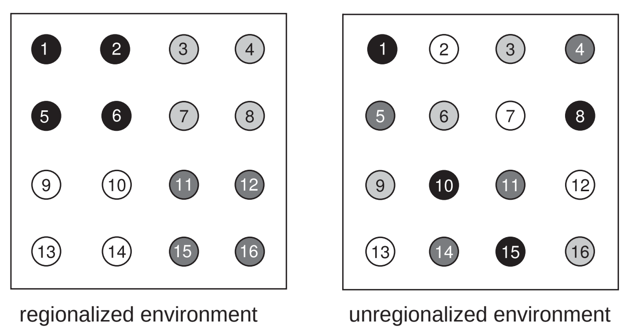


Fig. 4. Left: schematic map of the regionalized environment. The circles represent the positions of the 16 showcases; the 4 different shades of gray represent the 4 different object categories of the landmarks. Landmarks belonging to the same category were neighboring each other, thus forming 4 semantic regions within the regionalized environment; right: schematic layout of the unregionalized environment. The landmarks were pseudo-randomly distributed about the environment.

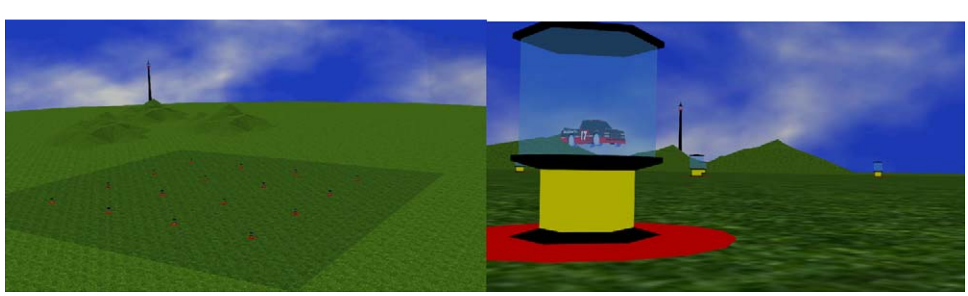


Fig. 3. Left: birds eye view of the virtual environment, the 16 showcases were arranged on a regular grid; right: subjects' perspective with a showcase and global landmarks (hills in the background).

Table 1
The three search sequences (S1–S3)

Trial	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
S1	4	15	2	9	16	7	13	11	5	14	3	12	1	8	10	16
S2	10	1	12	14	3	9	7	16	6	13	11	4	5	15	2	13
S3	6	4	14	1	7	9	16	3	10	8	2	11	14	13	5	15
Trial	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
S1	9	7	14	5	4	11	2	8	15	6	13	12	1	10	3	16
S2	11	1	8	10	3	16	9	7	14	5	15	4	6	12	2	13
S3	8	1	10	16	7	14	5	11	4	6	13	12	3	9	2	15

The numbers refer to the positions of showcases in Fig. 4.

object was presented as an image, that was superimposed on the projection screen. By actively navigating through the virtual environment, subjects searched for the showcase containing the target object. The trial ended when subjects entered a nonvisible circular area of 3.5 m radius surrounding the showcase that contained the target object. Subjects were instructed to complete the navigation task using the shortest possible path. In each of two experimental blocks, subjects had to visit each of the 16 objects once. Table 1 presents the sequences in which subjects had to search for the objects, the numbers correspond to the number of the showcases in the virtual environment and are independent of the experimental condition (see Fig. 4). Three different sequences (s1, s2, s3) were introduced to control for specific effects elicited by the sequence in which target locations had to be visited.

3.2.3. Variable of interest and predictions

Variable of interest: Subjects' trajectories were recorded during the navigation tasks. For each navigation task also the shortest possible path between starting place and target place was computed. By dividing the length of the travelled trajectory by the length of the shortest possible path and subtracting 1 an overshoot value was obtained. By multiplying the resulting value with 100 the overshoot in percent was obtained. An overshoot of 100% therefore corresponded to a path that had twice the length of the shortest possible path. The overshoot values were analysed as a function of the trials, thus representing subjects' learning of the virtual environment. The main interest concerned the comparison of overshoot values between the two experimental groups. From the recorded trajectories also the number and identity of places visited by subjects was reconstructed for each navigation task.

Predictions: If regions within an environment were perceived early during the process of learning that environment, it was expected that subjects from the regionalized condition encoded the regional information as soon as possible. That is, because (i) regional knowledge structures the environment, thus the learning of that environment should be facilitated, and (ii) regional knowledge allows applying search strategies that could compensate for missing or imprecise spatial knowledge at the detailed level. For example, the search for a specific landmark could be restricted to the region containing landmarks of the same object category. Taken together, it was expected that subjects from the regionalized condition, once they had perceived and encoded the regions, showed better searching and faster learning performance than subjects from the unregionalized condition.

3.2.4. Participants

In total, 44 subjects (mean age 24.5 years) were randomly assigned to one of two experimental groups, with 22 subjects in each group. Both groups were balanced with respect to gender. Subjects were mostly students from the University of Tübingen and were paid 8 Euro an hour.

3.2.5. Statistical analysis

Data were analysed using the open source statistics software 'R' (http://www.r-project.org) and the Unix program ANOVA. The error-bars of all data plots in this experiment display the standard errors of the mean (s.e.m.).

3.3. Results

Overshoot: Fig. 5 represents subjects' overshoot performance for both of the experimental groups as a function of the trials. By pooling over all 32 search trials a single overshoot value for each of the two experimental groups was obtained. The average overshoot for the regionalized group was 72.0%, the average overshoot for the unregionalized group was 142.3%. The average overshoot of block 1 (trials 1–16) was 108.4% for the regionalized group and 207.7% for the unregionalized group. In block 2 (trial 17–32), the average overshoot was 37.7% for the regionalized group and

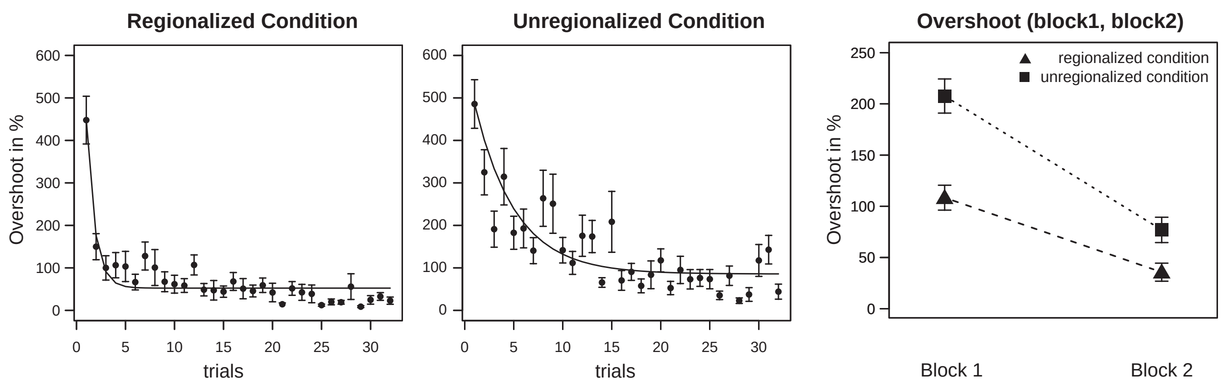


Fig. 5. Left: subjects' overshoot values as a function of the trials for both, the regionalized and the unregionalized condition. The solid lines display the exponential fits; right: subjects' overshoot values for the experimental groups and the experimental blocks.

76.9% for the unregionalized group. An analysis of variance (ANOVA) revealed a significant main effect of the experimental conditions (regionalized and unregionalized [$F(1,40) = 18.9$, $p < .001$]), a significant main effect of the experimental blocks [$F(1,40) = 166.9$, $p < .001$] and a significant groups $\times$ blocks interaction [$F(1,40) = 13.6$, $p = .001$]. No effect of gender could be found (male overshoot: 94.3%, female overshoot: 120.0%) [$F(1,40) = 2.5$, $p = .12$], nor an effect of the different sequences [$F(2,41) = 1.2$, $p = .40$].

While subjects from both experimental groups showed comparable navigation performance in the first trial of the experiment (overshoot regionalized: 450.5%, overshoot unregionalized: 487.4%, t-test: $t = -.392$, df $= 41.988$, p-value $= .697$), already in the second experimental trial, subjects from the regionalized condition showed better navigation performance than subjects from the unregionalized condition (overshoot regionalized: 151.7%, overshoot unregionalized: 326.7%, t-test: $t = -2.3647$, df $= 33.58$, p-value $= .02$).

In order to further quantify the difference between the experimental groups, subjects' learning behavior was described by an exponential function of the form

$$l(t) - l_0 + (l_1 - l_0)\mathrm{e}^{-(t-1)/\tau},$$

where t is the trials, l_1 the overshoot measured at trial 1, l_0 the residual overshoot after prolonged learning (after 32 trials), and τ the learning rate.

By fitting l_0 and τ separately for both data sets, τ-values of 0.86 (regionalized) and 4.18 (unregionalized) and l_0-values of 52.5 (regionalized) and 85.7 (unregionalized) were obtained. The corresponding fits are displayed in Fig. 5. The difference of l_1 and l_0 was defined as the learning range during the experiment. From the learning rate, the time $t_{0.5}$ can be calculated after which half of the overshoot reduction is achieved:

$$t_{0.5} = 1 + \tau \ln 2.$$

Calculating the time $t_{0.5}$ required for half of the overshoot reduction for both of the experimental groups, allowed to compare learning performance, independent of the initial overshoot (l_1) and the residual overshoot (l_0). For the regionalized group $t_{0.5}$ was 1.6, for the unregionalized group $t_{0.5}$ was 3.9. That is to say, subjects from the regionalized condition required only 1.6 trials for half of the overshoot reduction, while subjects from the unregionalized group required 3.9 trials.

Showcases visited: During the first trial of the experiment, subjects from the regionalized condition have visited 9.9 different showcases, while subjects from the unregionalized condition have visited 10.3 different showcases. That is, on average subjects from both of the experimental conditions have seen comparable proportions of all showcases within the environment in the first trial of the experiment (regionalized condition 61.9%, unregionalized condition 64.4%). However, subjects from the regionalized condition showed significantly lower overshoot-data in the second trial as compared to subjects from the unregionalized condition. A possible explanation for this effect is that subjects from the regionalized condition had an improved memory for the exact positions of showcases they had visited in the first trial. If the target of the second trial has already been visited in the first trial, subjects from the regionalized condition would then show better navigation performance.

The second trials of all subjects were therefore split in two groups, depending on whether or not the target of the second trial had already been visited in the first trial. The 'match group' contained all second trials of which the target had already been visited in the first trial. The 'no-match group' contained all second trials of which the target had not been visited in the first trial. Fig. 6 displays subjects' overshoot data for both of the experimental conditions and for the 'match group' and the 'no-match group'. Neither subjects from the regionalized nor from the unregionalized group benefited from visiting the second trial's target place already during the first trial (see Fig. 6). Subjects from the

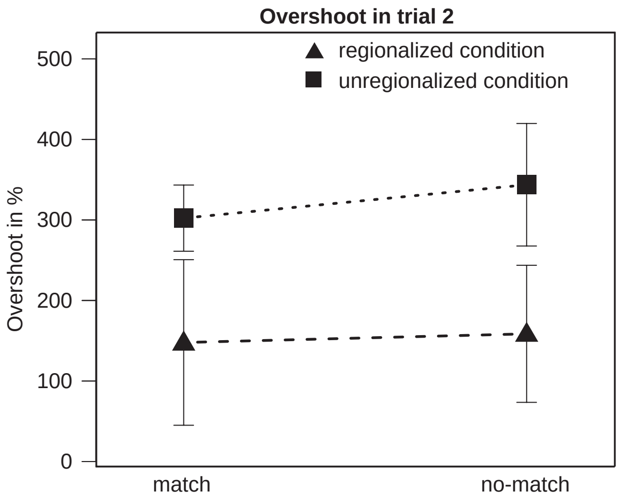


Fig. 6. Overshoot in the second trial for both of the experimental groups depending on whether or not subjects have visited the target of the second trial already during the first trial.

regionalized group showed an overshoot performance of 147.8% in the ‘match’ trials and 158.6% in ‘no-match’ trials (Wilcoxon rank sum test: $p = .62$). Subjects from the unregionalized group showed an overshoot performance of 302.2% in the ‘match’ trials and 343.7% in ‘no-match’ trials (Wilcoxon rank sum test: $p = .85$)

3.4. Discussion

The results of this experiment have shown faster learning- and better searching performance for subjects who had learned a virtual environment that was divided into different regions as compared to subjects who had learned a very similar virtual environment that did not contain regions. While in the first trial subjects from both of these experimental groups have shown comparable searching performance, already in the second trial, subjects from the regionalized condition showed better performance than subjects from the unregionalized condition. It is important to note that subjects' performance in the second trial did not depend on whether or not they had visited the second trial's target already during the first trial. This demonstrates that the difference in performance between the experimental groups did not result from faster learning of the exact positions of single objects within the regionalized environment. It is rather suggested that already during the first trial, in which subjects from both of the experimental conditions have visited more than 60% of the environment, the regionalized group has perceived and encoded the regions within the environment. Such regional knowledge structures the space and could therefore facilitate the learning of the environment. Moreover, the existence of regional knowledge allows to apply navigation- and search-strategies in order to overcome missing or imprecise information about the environment. For example, in this experiment regional knowledge allowed to assign a target location to a region by simply analysing the target's object category, even if that target had not been visited before. In order to find the target, subjects could then limit their search space to the appropriate region.

The results of this experiment suggest one function of hierarchies in spatial memory for navigation: hierarchal organization of spatial memory facilitates the learning of an environment by (i) structuring space and (ii) by providing the basis for search strategies that could overcome missing or imprecise spatial information.

4. Interaction of navigation strategies 1 (Experiment 2)

4.1. Purpose

In Experiment 1, the formation of hierarchical components, i.e. regional information, in human spatial memory was studied by simple search tasks in a regionalized environment. Here the use and interaction of different navigation- and route planning strategies that are applied after learning a regionalized environment are studied. It is proposed that in complex route planning tasks with multiple targets, comparable to shopping routes, different navigation- and route planning-strategies interact.

This experiment particularly concentrated on the use and interaction of two navigation strategies: (i) Gallistel and Cramer (1996) have shown that vervet monkeys, when having the choice to first visit a rich or a poor food patch, always go for the rich food patch first (see Section 1). Here it is studied whether such a navigation strategy, which is referred to as the *cluster*-strategy, is also employed by human navigators when faced with similar tasks; (ii) Wiener and Mallot (2003) developed the *fine-to-coarse* planning heuristic, a cognitive model of region-based route planning. Essentially the *fine-to-coarse* heuristic states that during route planning, fine space information (e.g. places) is used for nearby locations only, while coarse space information (e.g. regions) is used for distant locations (see Section 1).

The predictions of the *cluster*-strategy and the *fine-to-coarse* planning heuristic for the navigation-tasks in this experiment are explained below.

4.2. Methods

4.2.1. The virtual environments

The virtual environment consisted of 4 islands containing 4 places each. The places were interconnected by roads and bridges and could be identified by associated, unique landmarks (see Fig. 7). The landmarks of the four islands were of four distinct

Fig. 7. Left: schematic map of the virtual environment. Places are displayed as numbered circles, streets and bridges are represented by lines, the gray rectangles represent the islands or regions, respectively; middle: bird's eye view of the environment; right: subjects' perspective with a pop-up-landmark.

categories. While the landmarks of one island were of the category cars, the landmarks of the other islands were of the categories flowers, animals and buildings. The clustering of landmarks belonging to the same category, as well as the existence of four separated islands, ought to facilitate subjects' learning of the environment and ought to establish environmental regions within subjects' spatial memory. Landmarks were only visible when subjects were in close proximity, i.e. at the corresponding place, and are therefore referred to as pop-up landmarks. Subjects' movements were restricted to roads and bridges.

4.2.2. Procedure

Subjects had to go through an exploration- and a training-phase before entering the test-phase. During the 10 min exploration phase subjects could freely explore the environment. They were instructed to move through the environment, pay attention to the landmarks and learn the layout of the environment and the positions of the landmarks. The training phase was introduced to ensure that subjects had learned the environment before they entered the test phase. In the training phase, subjects were asked to complete six navigation tasks taking the shortest possible routes. For each training route subjects were teleported to the starting place of the route. The target place was specified by presenting a picture of the landmark associated with the target place. The image was superimposed on the screen. If subjects failed to find the shortest possible route, an error was recorded and the navigation task was repeated until subjects solved the task taking the shortest possible route. Note that in the experimental environment training tasks had multiple solutions.

During the test phase subjects were repeatedly asked to navigate the shortest possible route connecting their current position with three places in the environment. According to the spatial configuration of the starting place and the three target places, the navigation tasks were classified as belonging to either the test routes or to the distractor routes (see Fig. 8 and Table 2). While two

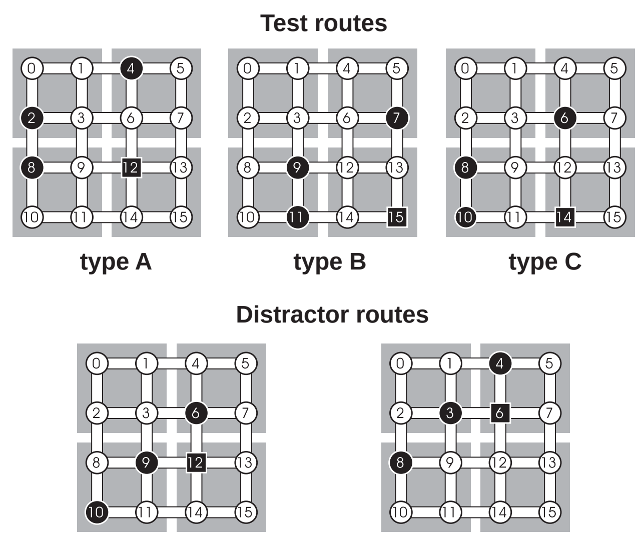


Fig. 8. Upper row: types A–C test routes: the black square represents the starting place, the black circles represent the target places; type A routes always started from one of the four inner-places (start place was 3, 6, 9 or 12), type B routes always started from one of the outer-places (start place was 0, 5, 10 or 15) and type C routes started from one of the intermediate places (start place was 1, 2, 4, 7, 8, 11, 13 or 14); lower row: distractor routes, displayed are two examples of the distractor routes.

of the three target places of the test routes were neighboring each other, thus forming a spatial cluster, the remaining target place was sole. The test routes could additionally be assigned to one of three subtypes, depending on the position of the starting place. Test routes of type A always started from one of the four inner places (start place was 3, 6, 9 or 12; see Fig. 7), test routes of type B always started from one of the outer places (start place was 0, 5, 10 or 15; see Fig. 7) and test routes of type C started from one of the intermediate places (start place was 1, 2, 4, 7, 8, 11, 13 or 14; see Fig. 7). Note that the spatial configuration of start- and target places was identical for routes of types A–C. By rotating and mirroring the configuration of start- and target places eight different test routes for each route

Table 2
The table lists all test-routes and all distractor-routes

Route type	Start place (target places)
A	12 (4,2,8), 9 (1,4,13), 12 (4,1,8), 6 (2,8,14), 9 (13,7,1), 3 (11,14,7), 6 (14,11,2), 3 (13,7,11)
B	15 (7,9,11), 10 (14,2,3), 15 (11,6,7), 5 (13,1,3), 10 (2,12,14), 0 (4,8,9), 5 (12,13,1), 0 (4,6,8)
C	14 (6,8,10), 8 (12,0,1), 13 (9,4,5), 4 (12,0,2), 11 (3,13,15), 2 (6,11,10), 7 (14,15,3), 1 (5,7,9)
Distractor-routes	9 (3,12,15), 3 (6,9,10), 12 (6,9,10), 6 (3,12,15), 9 (12,3,0), 3 (9,6,5), 12 (9,6,5), 6 (12,3,0), 3 (1,6,13), 6 (7,12,11), 12 (14,9,2), 9 (11,12,7), 3 (2,9,14), 6(4,3,8), 12 (13,6,1), 9 (8,3,4)

The starting place is followed by the three target places (in brackets). The numbers correspond to the place numbers in the schematized drawings of the environment (see Fig. 7).

type were generated. All test routes allowed for alternative solutions of equal length. A detailed description of all test routes can be found in Table 2.

The distractor routes were introduced to impede subjects' learning of the spatial configuration of start and target places of the test routes. Distractor routes had a single optimal solution only, not allowing for alternative solutions of equal length. Again, by rotating and mirroring the configuration of start- and target places a total of 16 different distractor routes were generated. A detailed description of all distractor routes can be found in Table 2.

Subjects were randomly assigned to one of two experimental groups. While subjects of experimental group 1 navigated types A and B test routes, subjects of experimental group 2 navigated types A and C test routes. In addition both groups also navigated all 16 distractor routes. In each of two experimental blocks subjects navigated four test routes of type A, four test routes of type B (experimental group 1) or four test routes of type A and four test routes of type C (experimental group 2), respectively, and eight distractor routes.

After subjects completed a test route they were teleported to the start place of the subsequent test route. For each test route multiple solutions of equal length were possible, whose initial directions differed by 90°. The initial heading of the subjects was in the middle of the route alternatives, which therefore appeared at visual angles 45° left and 45° right.

4.2.3. Variable of interest and predictions

Variable of Interest: as stated above, all test routes allowed for alternative solutions of equal metric length. One of the main characteristics discriminating these alternative solutions was whether subjects first passed by the clustered target-places or the sole target-place. Subjects' tendency to first pass the spatially clustered targets was evaluated. Since only correct navigations were included in the analysis, chance level with respect to first passing the clustered targets was 50%.

Predictions: the proposed *cluster*-strategy and the *fine-to-coarse* planning heuristic made different predictions for the navigation tasks.

The *cluster*-strategy states that subjects preferred to visit as many targets as fast as possible. This strategy predicted that subjects first visited the spatially clustered targets in all types of test routes (types A–C). On might expect a modulation of the effect size between types A–C routes. In type A routes the spatially clustered targets are distributed about two islands and might therefore be less apparent as compared to types B and C routes.

As stated in the introduction, the *fine-to-coarse* planning heuristic proposes that route planning takes place in a *focal representation* that represents both, fine space information (place-connectivity) for the current and close locations and coarse space information (region-connectivity) for distant locations. Fig. 9 demonstrates how such a *focal representation* is generated from hierarchical reference memory for routes of type B and routes of type C. In focal representations places located in distant regions are represented by super ordinate entities (e.g. regions). The actual route planning algorithm does not distinguish between places and regions, but plans towards the closest target (place or region). For all three route types the clustered and the sole target places were equidistant from the starting place. However, the region containing the clustered targets is closer than the region containing the sole target for routes of type C only (see Fig. 9). For routes of types A and B both target regions were equidistant from the start point. The *fine-to-coarse* heuristic therefore proposed that subjects first passed the clustered targets in routes of type C, while it predicted that subjects performed at chance level for routes of type A and for routes of type B.

Note that coarse-to-fine route planning schemes (see Section 1) do not predict any systematic effect, since first a coarse plan is generated solely at the region level, which is then refined. However, at the region-level routes of types A–C do not differ (see Fig. 9 for routes of types A and C).

4.2.4. Participants

Forty subjects (mean age 24.0 years) were randomly assigned to one of two experimental groups, with 20 subjects per group. Both groups were balanced with

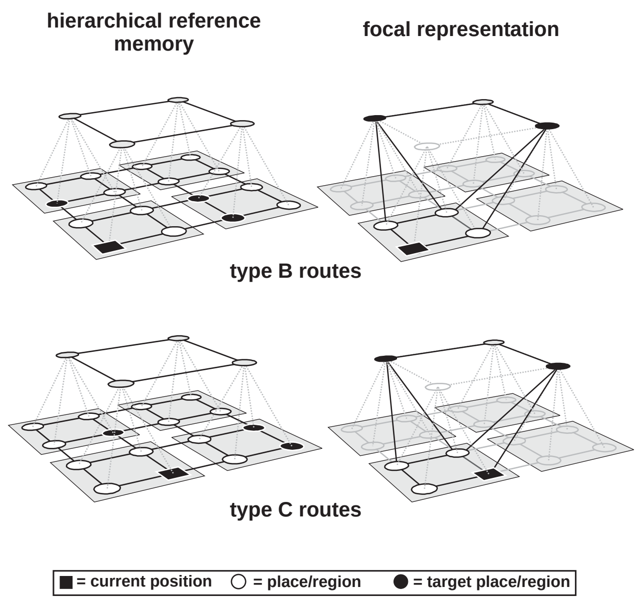


Fig. 9. Generating a focal representation for routes of type B (upper row) and routes of type C (lower row). Left column: superimposed on the hierarchical reference memory is a navigation task of types B and C: the black rectangle represents the observer or starting position, respectively, the black circles represent the target places; right column: the black edges and the black circled nodes represent the *focal representations* in which the route is planned. Only places from the current region are represented at the finest resolution, while distant locations are represented by the region they reside in. Distant target places are also represented by their region. Note that in the *focal representation* of type B routes, both target regions were equidistant from the starting place, while for type C routes the target regions were not equidistant from the starting place.

respect to gender. Subjects were mostly students of the University of Tübingen; they were paid 8 Euro per hour.

4.2.5. Statistical analysis

Data were analysed using the open source statistics software 'R' (http://www.r-project.org). The data were obtained in a repeated measures design. With single data points being binary variables, even after pooling across single trials a normal distribution was not given. Therefore, the nonparametric Wilcoxon's signed rank test was applied to the data when comparing to a given chance level and the Wilcoxon rank sum test was applied for comparison between groups. Using the 'exactRankTests'-package for R it was corrected for ties (available from: http://www.cran.au.r-project.org).

4.3. Results

Training routes: If a training route was not completed using the shortest possible route, the trial was recorded as an error and repeated. Subjects' performance during training was measured by counting the repetitions of training trials. On average subjects made 2.2 errors during the training phase. The experimental groups did not differ in their error-rate (experimental group 1: 2.0 errors, experimental group 2: 2.5 errors; Wilcoxon rank sum test: $p = .14$) and were therefore pooled. Male subjects produced less errors during the 6 training trials than females (male errors: 1.2; female errors: 3.15; Wilcox rank sum test: $p = .002$).

Subjects' overall performance: subjects navigated 74.9% of the navigations in the test phase error-free, that is to say, subjects have found one of the alternative optimal routes. Female and male subjects did not differ in their performance during the test phase (females: 71.8% correct navigations, males: 77.9% correct navigations; Wilcoxon rank sum test: $p = .28$, see Fig. 10). Subjects' overall performance increased in the second experimental block as compared to the first experimental block (block 1: 68% correct navigations, block 2: 81.8%, Wilcox rank sum test: $p = .002$, see Fig. 10).

Subjects navigated correctly in 82.0% of the test-routes and in 67.8% of the distractor-routes (Wilcoxon rank sum test: $p = .08$). Below only error-free navigations of test routes were evaluated.

Test routes (types A–C routes): both of the experimental groups navigated test routes of type A during the test phase. A comparison of subjects' tendency to first pass by the clustered targets in type A routes did not differ between experimental group 1 and experimental group 2 (49.5%, 51.7%, $p = .73$). Test routes of type A were therefore pooled across experimental groups. Subjects performed at chance level with respect to first passing the spatially clustered targets when navigating routes of types A and B. (type A: 50.6%, Wilcoxon signed rank test against 50%: $p = .93$; type B: 51.8%, Wilcoxon signed rank test against 50%: $p = .67$). On the other hand, subjects clearly preferred to first pass the spatially clustered targets when navigating routes of type C (type C: 78.6%, Wilcoxon signed rank test against chance level (50%): $p < .001$, see Fig. 10). While a comparison of subjects' navigation behavior between the different route types did not reveal a difference for types A and B routes (Wilcoxon rank sum test: $p = .76$), it revealed a significant difference for both, types A and C comparison and types B and C comparison (type A routes vs. type C routes: Wilcoxon rank sum test: $p < .001$, type B routes vs. type C routes: Wilcoxon rank sum test: $p = .001$). Subjects' preference to first pass by the clustered targets when navigating type C routes did not differ between experimental blocks (block 1: 77.9%, block 2: 77.1%; Wilcoxon rank sum test: $p = .9$), nor between gender (female: 80.1%; male: 77.1%, Wilcoxon rank sum test: $p = .70$).

4.4. Discussion

This experiment was designed to study the influence of environmental regions and the distribution of target places within an environment on human route planning

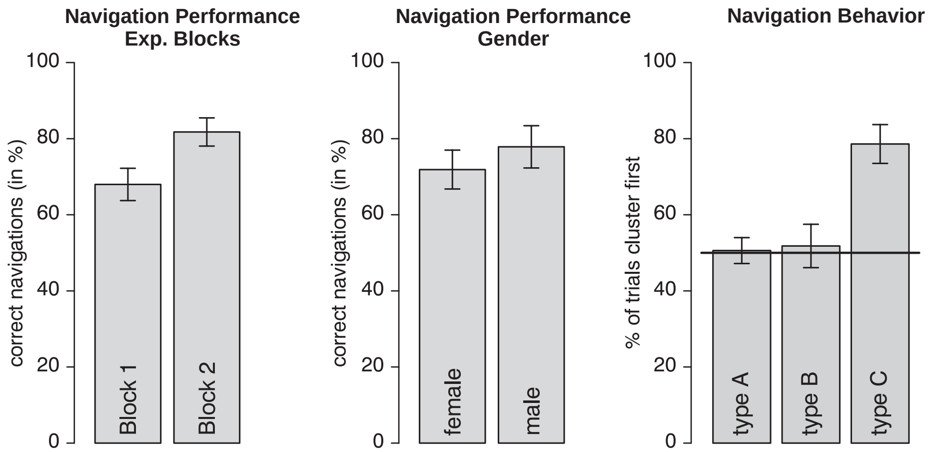


Fig. 10. Left: subjects' performance in experimental block 1 and experimental block 2. Here the percentages of correct navigations are displayed; middle: subjects' performance for male and female subjects; right: subjects' preference to first pass by the spatially clustered targets for the three types of test routes (types A, B and C).

behavior. Although all types of test route had two spatially clustered targets and one sole target, subjects chose to first visit the clustered targets in only one of the test route types. In both of the other types of test routes subjects' preference to first visit the clustered targets did not differ from chance level. Also, subjects' preference was not modulated depending on whether the clustered targets were distributed about two regions or located on the same region. These results suggest that the existence of spatially clustered targets did not influence subjects' route planning behavior in this experiment.

Subjects preferred to first pass the spatially clustered targets in routes of type C only. While in all route types the clustered targets and the sole target were equidistant from the starting place, only in routes of type C the region (the island) containing the clustered targets was closer than the region containing the sole target. This suggests that subjects planned their routes in order to enter the closest target region first, irrespective where exactly the targets were located within that region. These results are in line with the predictions of the *fine-to-coarse* planning heuristic, while they contradict coarse-to-fine planning schemes. As pointed out in Section 4.2.3 coarse-to-fine planning schemes first generate a coarse route plan at a high abstraction level of the representation that is refined successively. No route plan generated solely at the region level of the representation takes into account subject's position within the starting region, therefore a coarse-to-fine planning scheme would not predict any systematic effect for routes of types A–C. However, the results provide additional evidence for the notion that human route-planning is not based on place-connectivity alone, but takes into account region-connectivity.

An alternative explanation for the observed effect is given when comparing the complexity of alternative optimal solutions for routes of type C. In contrast to the ICD-complexity measure by O'Neill (1991), that measures the complexity of an entire environment in order to compare it to a second environment, here the complexity of alternative routes within the same environment was of interest. A rather crude measure of complexity for routes was used, by simply adding up the possible movement decisions along a path. A lower complexity therefore referred to a path that allows for fewer movement decisions. In routes of type C, paths that first passed the clustered targets provided fewer possible movement decisions than paths that first visited the sole target (see Table 3). That is to say, routes that first passed by the target cluster might have been judged as being less complex than routes that first passed by the sole target. If subjects took the complexity of alternative routes into account during route planning, e.g. in order to reduce the risk of getting lost during navigation, subjects preferred routes along the border of the environment. The strategy to minimize the complexity of a path during route planning is referred to as the *least-decision-load* strategy.

Since in this experiment the navigation tasks did not allow to discriminate between the *fine-to-coarse*- and *least-decision-load*-strategy, one also has to consider that both strategies discussed above (*fine-to-coarse*- and *least-decision-load*-strategy) could account for the observed effect, by, e.g. a linear combination.

5. Interaction of navigation strategies II (Experiment 3)

5.1. Purpose

In Experiment 2, a systematic effect in subjects' navigation behavior for routes of type C was revealed.

Table 3
Comparison of alternative optimal paths to solve type C routes

Strategy	Place	Place	Place	Place	Place	Place	Place	Complexity
Cluster	14 (3)	11 (3)	10 (2)	8 (3)	2 (3)	3 (4)	6	18
Cluster	14 (3)	11 (3)	10 (2)	8 (3)	9 (4)	3 (4)	6	19
Cluster	14 (3)	11 (3)	10 (2)	8 (3)	9 (4)	12 (4)	6	19
Sole	14 (3)	12 (4)	6 (4)	3 (4)	2 (3)	8 (3)	10	21
Sole	14 (3)	12 (4)	6 (4)	3 (4)	9 (4)	8 (3)	10	22
Sole	14 (3)	12 (4)	6 (4)	12 (4)	9 (4)	8 (3)	10	22

The first column indicates whether the clustered or the sole targets are visited first. The last column shows the sum of all possible movement decisions. The intermediate columns list the places along the routes, the number of possible movement decisions at the corresponding place are specified in brackets.

Two navigation strategies have been described that could have accounted for the observed effect. This experiment is a modification of Experiment 2. By changing the shape of the islands while keeping the absolute positions of the start-and target places of the test routes constant, the influence of the *fine-to-coarse* planning heuristic and the *least-decision-load*-strategy could be studied separately, as well as a possible interaction of these navigation strategies (as explained in detail in Section 5.2.3).

5.2. Methods

5.2.1. The virtual environment

The virtual environment used in this experiment was similar to the environment used in Experiment 2. The only difference was the shape of the islands, which were changed from a squared outline to triangle outlines (see Fig. 11). The landmarks were moved accordingly, such that still all landmarks of one island were of the same object category. As in Experiment 2, the landmarks were only visible when subjects were in close proximity, i.e. at the corresponding place.

5.2.2. Procedure

After the exploration- and training phase (identical to Experiment 2, see Section 4.2.2) subjects entered the test phase. During the test phase subjects navigated exactly the same routes as subjects from the experimental group 2 of Experiment 2 (see 4.2.2). That is to say, single routes had the same starting place and the same target places in Experiment 3 as in Experiment 2, irrespective of the shape of the islands (see Fig. 12). Changing the form of the islands resulted in a subdivision of the 2 types of test routes (types A and C) from Experiment 2 into 4 types of test routes in this experiment (see Fig. 12 and Table 4). Again, distractor routes were introduced to impede subjects' learning of the spatial configuration of start- and target places of the test routes. The same distractor routes were used that had already been used in Experiment 2.

As in Experiment 2, subjects navigated 32 routes during the test phase of this experiment; 16 routes were test routes (4 of each type of test routes, see Table 4), 16 routes were distractor routes. In each of two experimental blocks subjects navigated 2 routes of each of the 4 types of test routes and 8 distractor routes.

After subjects completed a test route they were teleported to the start place of the subsequent test route. For each test route multiple solutions of equal length were possible, whose initial directions differed by 90°. The initial heading of the subjects was in the middle of the route alternatives, which therefore appeared at visual angles 45° left and 45° right.

5.2.3. Variable of interest and predictions

Variable of interest: as in Experiment 2 all test routes allowed for alternative solutions of equal metric length. Again, subjects' tendency to first pass the spatially clustered targets was evaluated. Since only correct navigations were included in the analysis, chance level with respect to first passing the clustered targets was 50%.

Predictions: changing the shape of the island in this experiment as compared to Experiment 2, while keeping the absolute positions of start- and target-places constant, allowed to study the influence of the *fine-to-coarse*-planning strategy and the *least-decision-load* strategy separately, as well as an interaction of both of these strategies. While for routes of type C in Experiment 2 both the *fine-to-coarse*-planning strategy and the *least-decision-load*-strategy predicted that subjects first passed by the clustered targets, in this experiment the *fine-to-coarse*-strategy and the *least-decision-load*-strategy made different predictions for routes of types C1, A1 and A2, as explained below.

Since both regions containing targets were equidistant from the starting place and in adjacent regions, in routes of type C1, the *fine-to-coarse* strategy did not predict any systematic effect; the *least-decision-load*-strategy, on the other hand, predicted that subjects navigate along the border, therefore first passing the clustered targets.

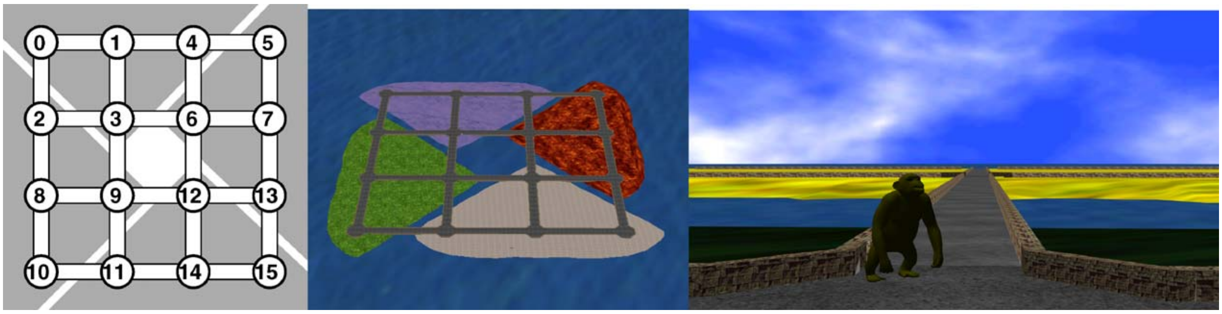


Fig. 11. Left: schematic map of the virtual environment. Places are displayed as numbered circles, streets and bridges are represented by lines, the gray triangles represent the islands or regions, respectively; middle: bird's eye view of the environment; right: subjects' perspective with a pop-up-landmark.

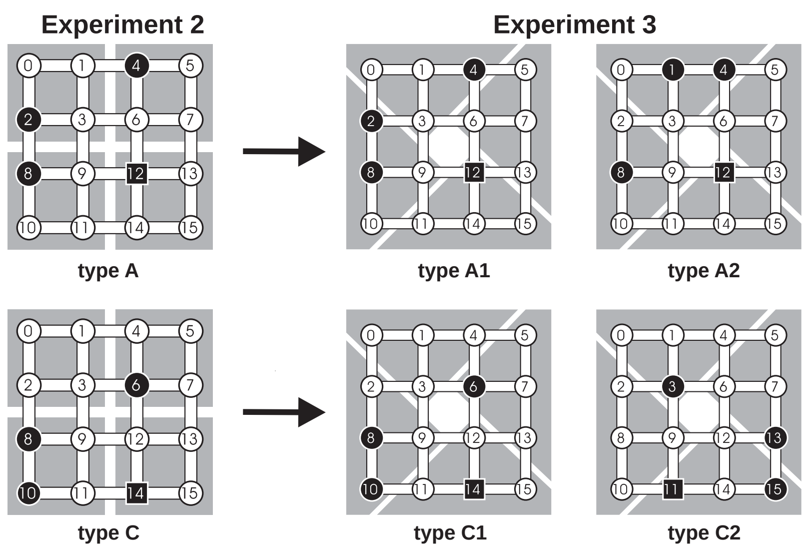


Fig. 12. The test routes: the black square represents the starting place; the black circles represent the target places. Depicted on the left is route type A and route type C of Experiment 2. By changing the form of the islands and by mirroring the route along the diagonal centerline, types A1 and A2 routes and types C1 and C2 routes were obtained. The *cluster*-strategy and *fine-to-coarse*-planning heuristic and the *least-decision-load*-strategy made different predictions for types A1, A2, C1 and C2 routes (see Section 5.2.3).

Table 4
The table lists all test-routes and all distractor-routes

Route type	Start place (target places)
A1	12 (4,2,8), 9 (1,4,13), 6 (14,11,2), 3(13,7,11)
A2	12 (4,1,8), 9 (13,7,1), 6 (2,8,14), 3 (11,14,7)
C1	14 (6,8,10), 7 (14,15,3), 1 (5,7,9), 8(12,0,1)
C2	13 (9,4,5), 4 (12,0,2), 11 (3,13,15), 2 (6,11,10)
Distractor-routes	9 (3,12,15), 3 (6,9,10), 12(6,9,10), 6(3,12,15), 9 (12,3,0), 3 (9,6,5) 12 (9,6,5), 6 (12,3,0), 3 (1,6,13), 6 (7,12,11), 12 (14,9,2), 9 (11,12,7), 3 (2,9,14), 6 (4,3,8), 12 (13,6,1), 9 (8,3,4)

The starting place is followed by the three target places (in brackets). The numbers correspond to the place numbers in the schematized drawings of the environment (see Fig. 11).

For routes of types A1 and A2, the *least-decision-load*-strategy did not predict any systematic effect. Paths with the same 'decision-load', i.e. the same number of possible movement decisions, were available, irrespective of whether subjects first passed the clustered or the sole target. However, for type A1 routes the *fine-to-coarse* strategy predicted that subjects first passed by the clustered targets, while for routes of type A2 the *fine-to-coarse* strategy predicted that subjects first passed by the sole target. In type A1 routes the clustered targets, and in type A2 routes the sole target, could be reached by crossing a single region boundary, while two region boundaries had to be crossed in order to reach the other targets (i.e. the sole target for type A1 routes and clustered targets for type A2 routes; see Fig. 12).

For routes of type C2, both the *least-decision-load*-strategy and the *fine-to-coarse*-planning strategy predicted the same navigation behavior. The *least-decision-load*-strategy predicted that subjects navigate along the border of the environment, therefore first passing the clustered targets. The *fine-to-coarse*-planning strategy predicted that subjects first passed by the clustered targets, because one of the corresponding target places resided in the starting region, while two region boundaries had to be crossed in order to first visit the sole target. If the *least-decision-load*- and the *fine-to-coarse*-planning strategy were linearly combined (as discussed in Section 4.4) a stronger preference for the clustered target was expected as compared to routes of type C1 in which only the *least-decision-load*-strategy predicted that subjects first pass by the clustered target places. Obviously, the *cluster*-strategy predicted that subjects first pass by the clustered targets for all route types.

5.2.4. Participants

Thirty subjects (mean age 23.2 years) participated in the experiment. Subjects were balanced with respect to gender. Most subjects were students of the University of Tübingen; they were paid 8 Euro per hour. Subjects that have already participated in Experiment 2 were not allowed to participate in this experiment.

5.2.5. Statistical analysis

See Section 4.2.5.

5.3. Results

Training routes: on average subjects made 1.8 errors during the training phase. Female and male subjects did not differ in their training performance (average male errors: 1.4, average female errors: 2.2; Wilcoxon rank sum test: $p = .22$).

Subjects' overall performance: in the test phase subjects produced 81.3% error-free trials, that is to say subjects found one of the alternative optimal routes. Female and male subjects did not differ in their performance (female: 75.4% correct navigations, male: 87.1% correct navigations; Wilcoxon rank sum test: $p = .07$). Subjects' overall performance increased in the second experimental block as compared to the first experimental block (block 1: 74.2% correct navigations, block 2: 88.3%, Wilcox rank sum test: $p < .01$). Subjects navigated 91.8% of the test routes correctly and 70.6% of the distractor routes (Wilcoxon rank sum test: $p < .001$). Below we evaluate the error-free navigations of the 4 types of test routes only.

Test routes: Table 5 and Fig. 13 summarize subjects' preference to first pass the spatially clustered targets for the different route types. Subjects significantly preferred to first pass the target cluster in routes of types A1, C1 and C2, while they performed at chance level (50%) for routes of type A2. A comparison of subjects' preference to first pass the target cluster between types A1 and A2 routes revealed a significant difference (Wilcoxon rank sum test: $p = .01$), a comparison of types C1 and C2 routes did not reveal a significant difference (Wilcoxon rank sum test: $p = .13$). Since subjects only navigated two routes of each test route type per block, performance for the experimental blocks was not analysed separately.

Table 5 also summarizes the effects of gender. Only for routes of type C1 a marginally significant difference between female and male subjects was found.

Comparison of results from Experiments 2 and 3: Experiments 2 and 3 only differed with respect to the shape of the island in the virtual environment. The configuration of start place and target places of the navigation tasks in the test phase was identical between experimental group 2 of Experiment 2 (the group that navigated types A and C routes) and the experimental group of Experiment 3. Therefore, data from both experiments were analysed together by comparing subjects' navigation behavior with the predictions of the three proposed navigation strategies (*cluster*-strategy, *least-decision-load*-strategy and *fine-to-coarse*-strategy).

Table 6 summarizes subjects' tendency to first pass the clustered targets for all route types of Experiments 2 and 3. Additionally, the three route planning strategies are listed and whether these strategies predicted that subjects first pass the clustered targets (1), the sole

Table 5
Left: the table summarizes subjects' preference to first pass by the spatially clustered target for the different route types and the *p*-values for the Wilcoxon signed rank test against chance level (50%); right: the table summarizes female and male navigation behavior separately

	Cluster first (%)	*p*-Value		Female (%)	Male (%)	*p*-Value
Type Al	69.7	.003	Type Al	71.1	68.3	.57
Type A2	51.9	.667	Type A2	48.8	55.0	.86
Type Cl	77.2	<.001	Type Cl	86.7	67.8	.0502
Type C2	88.1	<.001	Type C2	93.3	82.8	.16

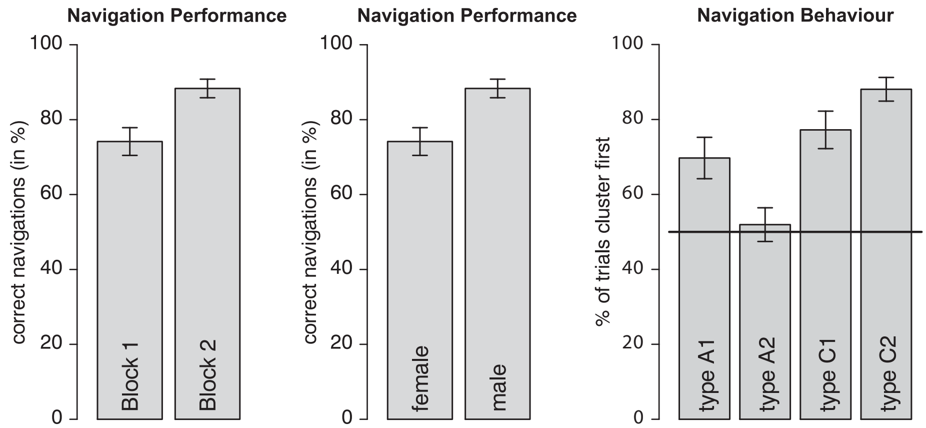


Fig. 13. Left: subjects' performance in experimental block 1 and experimental block 2. Here the percentage of correct navigations are displayed; middle: performance for female and male subjects; right: subjects' preference to first pass by the spatially clustered targets for the four types of test routes (types A1, A2, C1 and C2).

Table 6
The table displays the predictions of the proposed *cluster—least-decision-load-* and *fine-to-coarse*-strategy concerning whether or not subjects first pass by the clustered target (1 = yes, 0 = no, 0.5 = no prediction) for the different route types from experiments 2 and 3

	Cluster	Least-decision-load	Fine-to-coarse	Average strategy pred.	Navigation results (%)
Type A	1	0.5	0.5	0.66	50.60
Type B	1	0.5	0.5	0.66	51.70
Type C	1	1	1	1	78.60
Type Al	1	0.5	1	0.83	69.70
Type A2	1	0.5	0	0.5	51.90
Type Cl	1	1	0.5	0.83	77.20
Type C2	1	1	1	1	88.10

The average of the three hypotheses is displayed, as well as subjects' measured preference to first pass the target cluster.

target (0), or whether they did not predict any systematic preference (0.5). In Fig. 14 subjects' preference to first pass by the target cluster is plotted according to the predictions of the three strategies. Assuming the simplest combination (a linear combination with equal weights), the predictions of the three navigation strategies were averaged. Subjects' navigation behavior strongly correlated with the averaged predictions of the three navigation strategies ($r = .92$, $p < .01$).

5.4. Discussion

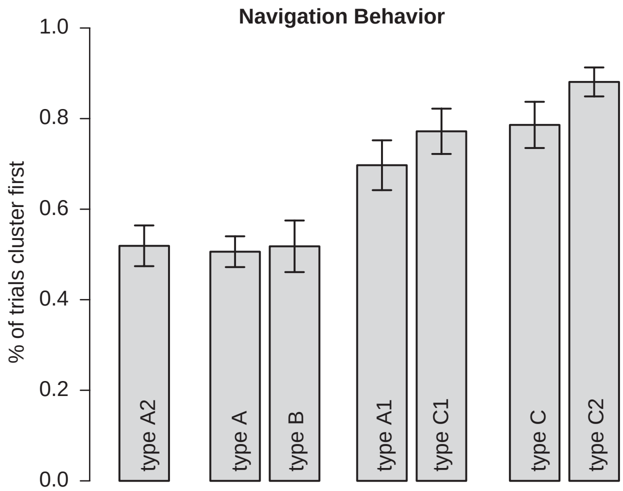
Subjects showed a significant preference to first pass by the spatially clustered targets in routes of types A1, C1, and C2, while they performed at chance level in routes of type A2. A comparison between subjects' navigation behavior and the predictions of the proposed navigation strategies reveals that none of the three navigation strategies alone could account for the empirical data, as explained below:

Least-decision-load-strategy: the *least-decision-load* strategy predicted that subjects first passed by the spatially clustered targets in routes of types C1 and C2, while no systematic effect was predicted for routes of types A1 and A2. The predictions matched the results for types A2, C1, and C2 routes, but did not match results for type A1 routes.

Cluster-strategy: the *cluster*-strategy predicted that subjects first visited the spatially clustered targets in all route types. These predictions matched the result of types A1, C1 and C2 routes, but did not match results of type A2 routes.

Fine-to-coarse planning heuristic: the *fine-to-coarse* strategy predicted that subjects first passed the spatially clustered targets in routes of type A1 and routes of type C2, while it predicted that subjects first passed the sole target in routes of type A2. For routes of type C1 no systematic effect was predicted. The predictions matched results for types A1 and C2 routes, but did not match results for types A2 and C1 routes.

Since none of the above navigation strategies alone could account for the results of the current experiment, and since no other navigation strategy was evident that could describe the effects, an interaction between multiple navigation strategies had to be assumed.



cluster	1	1	1	1	1	1	1
ldl	0.5	0.5	0.5	0.5	1	1	1
ftc	0	0.5	0.5	1	0.5	1	1
average	0.5	0.66	0.66	0.83	0.83	1	1

Fig. 14. The figure displays subjects' tendency to first pass by the clustered targets depending on the predictions of the three proposed navigation strategies (*cluster*, *least-decision-load* and *fine-to-coarse*). For each navigation strategy and for each route type the predictions are quoted (1 = first clustered targets, 0 = first sole target, 0.5 = no prediction).

This is best demonstrated by a comparison between subjects' behavior when navigating routes of types A1 and A2. The *fine-to-coarse* strategy predicted contradictory outcomes for routes of types A1 and A2, while the *least-decision-load*-strategy did not predict any systematic effects for these route types. If target clusters did not influence subjects' route planning behavior (as suggested in Experiment 2) and if subjects planned their routes in order to enter the closest target region first (as suggested by the *fine-to-coarse* planning heuristic; see Experiment 2), they should have first passed by the clustered targets in routes of type A1, while they should have first passed by the sole target in routes of type A2. In fact, results for type A1 routes matched the above predictions, while results for type A2 routes did not. Rather than preferring to first pass by the sole target when navigating routes of type A2, subjects behaved at chance level, choosing to first pass the sole and the clustered targets equally often.

The discrepancies between predictions and results could be accounted for if one assumed that in the current experiments the *fine-to-coarse* planning heuristic, the *cluster*-strategy and the *least-decision-load*-strategy interacted.

Linearly combined, the *cluster*-strategy and the *fine-to-coarse* planning heuristic would add up in routes of type A1, while they would cancel each other out in routes of type A2, exactly predicting the empirical data. The *least-decision-load*-strategy made no prediction for routes of types A1 and A2.

In routes of types C1 and C2 subjects preferred to first pass by the target cluster. Again, linearly combined, the *cluster*- and *least-decision-load*-effect add up in routes of type C1, both predicting that subjects first passed by the target cluster, while the *fine-to-coarse*-strategy did not predict a systematic effect. In type C2-routes all three navigation strategies (*cluster*-, *least-decision-load*- and *fine-to-coarse*-strategy) predicted that subjects first passed by the target cluster. In fact, although not statistically reliable, in routes of type C2, in which all three strategies predicted a preference to first pass by the clustered targets, the results revealed a stronger effect than in type C1 routes, in which only two strategies predicted a preference to first pass by the clustered targets. Again, this trend indicates that all three strategies are combined.

It is therefore argued that in Experiment 3 the *cluster*-strategy did influence subjects' navigation behavior, while the *cluster*-strategy did not influence subjects' navigation behavior in Experiment 2. Such a strategy shift is in line with earlier results of Golledge (1995), who has shown that human navigators use different route selection criteria in different environments and on different routes. A possible explanation for this strategy shift is given by Werner and Long (2003) who have shown that the misalignment of local reference systems does result in wayfinding problems and difficulties to understand the overall layout of the environmental structure. In their study Werner and Long investigated the structure of the town hall in Göttingen. The layout of the corresponding floor plan reveals that the elevator is rotated about 45° with respect to the gangways in the floor. That is to say, the salient main axes of the elevator are misaligned with the salient axis of the floor. A user might therefore choose a spatial reference system upon exiting the elevator that is not appropriate for the rest of the floor. Werner and Long argued that the misalignment of different parts within an environment makes integration of spatial knowledge very difficult. In Experiment 3, the main axes of the islands were rotated about 45° with respect to the street grid. Although this misalignment of spatial reference systems did not impede subjects' wayfinding performance, understanding the overall structure of the environment was more difficult in Experiment 3 than in Experiment 2 (informal interviews with subjects after the experiments). These facts could account for the use of different navigation strategies, or a different weighting of the three navigation strategies in Experiment 3 as compared to Experiment 2.

However, if all route types of Experiments 2 and 3 are analysed together with respect to the average prediction of the three navigation strategies, a highly significant correlation was found. That is to say, a simple linear combination of the *cluster*, the *least-decision-load*- and the *fine-to-coarse*-strategy with equal weights is sufficient to closely predict subjects' navigation behavior in both experiments.

6. Conclusions

In this work, 3 navigation experiments were presented that investigated the use of navigation strategies both during the learning of an environment (Experiment 1) and during subsequent route planning tasks (Experiments 2 and 3). Special interest in all of the experiments concerned the role of environmental regions for human navigation.

The results of Experiment 1 suggest that environmental regions were perceived and encoded very early during the process of learning an environment. This result is in line with the hierarchical theories of spatial memory (e.g. Stevens & Coupe, 1978; McNamara et al., 1989; Hirtle & Jonides, 1985). It was argued that regional knowledge not only structures space but also allows the employment of search strategies in order to overcome missing or imprecise spatial knowledge at the detailed level, revealing a possible function of the hierarchical organization of spatial memory for navigation.

In Experiments 2 and 3, the interaction of multiple navigation strategies was studied. In addition to the *fine-to-coarse* planning heuristic (Wiener & Mallot, 2003), two other navigation strategies were identified that influenced subjects' navigation behavior, the *least-decision-load*-strategy, and the *cluster*-strategy (Gallistel & Cramer, 1996). The supporting evidence for the use of the *fine-to-coarse* planning heuristic confirms the notion that human route planning takes into account region-connectivity and is not based on place-connectivity alone. This suggests a second function of the hierarchical organization of spatial memory for navigation, namely the reduction of the complexity of route planning tasks. The *least-decision-load*-strategy states that subjects, when having the choice between alternative paths, choose the path that minimizes the number of possible movement decisions. Such a strategy could be employed, because the risk of getting lost is smaller on less complex routes. The *cluster*-strategy states that human route planning takes into account the distribution of target locations within an environment, resulting in a preference for paths that allow visiting as many target places as fast as possible.

Acknowledgements

This study was supported by the DFG (Deutsche Forschungsgemeinschaft)—MA 1038/9-1.

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