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PEER-REVIEWED ARTICLE

The Relationship Between Scale and Strategy in Search-Based Wayfinding

Thomas J. Pingel
Northern Illinois University
tpingel@niu.edu

Victor R. Schinazi
ETH Zürich
victor.schinazi@gess.ethz.ch

We present the results of a study that investigated the interaction of strategy and scale on search quality and efficiency for vista-scale spaces. The experiment was designed such that sighted participants were required to locate "invisible" objects whose locations were marked only with audio cues, thus enabling sight to be used for search coordination, but not for object detection. Participants were assigned to one of three conditions: a small indoor space (~20 m²), a medium-sized outdoor space (~250 m²), or a large outdoor space (~1000 m²), and the entire search for each participant was recorded either by a laser tracking system (indoor) or by GPS (outdoor). Results revealed a clear relationship between the size of space and search strategy. Individuals were likely to use ad-hoc methods in smaller spaces, but they were much more likely to search large spaces in a systematic fashion. In the smallest space, 21.5% of individuals used a systematic gridline search, but the rate increased to 56.2% for the medium-sized space, and 66.7% for the large-sized space. Similarly, individuals were much more likely to revisit previously found locations in small spaces, but avoided doing so in large spaces, instead devoting proportionally more time to search. Our results suggest that even within vista-scale spaces, perceived transport costs increase at a decreasing rate with distance, resulting in a distinct shift in exploration strategy type.

INTRODUCTION

Modern navigation systems have, to a large degree, solved many of the technical limitations associated with wayfinding. GPS-enabled smartphones are ubiquitous, and are responsive to many user preferences, including least-time, shortest-distance, and preference for certain kinds of paths, among many others. In addition to preferences, differences in strategy have been invoked to explain differences in wayfinding behavior. Common examples of these include heuristics such as least-angle estimation (Hochmair 2005), higher order strategy sets (Lawton 1994), and personality influences (Pingel 2012).

Here, we investigate the role of scale and strategy in search-based wayfinding. Search-based wayfinding involves goal directed movement to a target with an unknown location and is distinct from access-based wayfinding in which the location of the target is known (Passini 1992). Although the conceptual difference between these two is clear, in practice the differences may be somewhat less distinct. Spatial knowledge is often imprecise, and many destinations are entirely new to the traveler (Montello 2005). The grey area between search and access-based wayfinding is perhaps best glimpsed when one considers the phenomenon of being "unknown lost," in which an individual has a belief about their position in the environment that is, in fact, mistaken (Crampton 1988).

Search is an integral part of navigation. This is particularly true during wayfinding, given that it often occurs on a continuum between unknown and known target locations in the environment, and with varying degrees of familiarity with the environment itself (Allen 1999). Wiener, Büchner, and Hölscher (2009) describe a complete taxonomy of wayfinding in which search is described as a type of wayfinding directed at a specific target where destination knowledge is unavailable. Just as the degree of knowledge of the environment or of target location will result in observable differences in wayfinding behavior, the extent or scale of the space permeates the problem, as individuals are likely to strategize differently at a local scale of travel than they will at a larger scale. Previous work (Tellevik 1992; Hill et al. 1993; Gaunet and Thinus-Blanc 1996) has identified how strategy impacts spatial layout learning and wayfinding at room-sized spaces. We extend this work by examining how larger spaces impact strategic behavior and how strategic reasoning changes as the size of the problem space increases.

BACKGROUND

Much of the early work on spatial search and evasion strategy originated in response to World War II, and the problem of locating the machines of war. Koopman (1956a; 1956b; 1957) and Gould (1966) provided the mathematical basis for search in both real world contexts and in information theory. Within real-world contexts, Koopman found that the inverse of the cube of the distance between the searcher and the target was proportional to the probability of detection for many types of distance-detection schemes, including visual, sonar, and radar searches. This inverse cube law still serves as the basis for modern search and rescue operations (National Search and Rescue Committee 2000; Hill, Carl, and Champagne 2006). Much of Koopman's work was adapted by Isaacs (1965) and Gal (1979; 1980) to create spatially explicit game theoretic models.

An important element in search for stationary targets is the avoidance of searching the same space more than necessary. Truly random searches disobey this central tenant, and as such are relatively inefficient. Given the relatively high costs of conducting large-scale searches (of opposing military hardware, persons lost in the wilderness, drug interdiction, or any other well-hidden object), many systematic strategies of searching exist. Perhaps the most common of these is the parallel or gridline search (Koopman 1956b; Hill et al. 1993), which is most useful when no information about the location of the target is known. This search pattern manifests as a series of parallel transects, and is common to nearly every search environment (National Search and Rescue Committee 2000). The distance between parallels, or track spacing, is determined by a detection function, which tends to be high near the searcher and drop to zero some distance away, and is influenced by the method of detection and other characteristics of the searcher, the target, and the environment. When more specific information about the location of the target is known, an improved strategy is to make an initial guess about the location of the target followed by outward-moving concentric squares or circles. This tends to concentrate the search in the most likely areas first, leaving less likely areas last. In conditions where detection is particularly difficult (i.e., where probability of detection is significantly less than one, even at the maximum), repeated searches of the same space are often justified.

In many cases, large areas are subdivided into smaller spaces, to which any of the above systematic searches may be applied. These segmented spatial search strategies may take a variety of forms, with sector searches and rectilinear subdivisions the most common. In addition, most of the above strategies assume adequate personal or map-based knowledge of the area in question. When this is not the case, perimeter searches are often quite valuable in learning the overall spatial layout (Hill et al. 1993), and can be combined with inward spiraling square or circular patterns to exhaustively search the space.

Heth and Cornell (1998) describe the ways in which an understanding of lost person behavior constrains search and rescue efforts to minimize search time and cost, and maximize the preservation of life. The use of a geographic information system as an aid to planning and conducting a search allows for a non-uniform treatment of a search area, so that simple spatial patterns, like the gridline search, can be targeted (Heth and Cornell 2007). Heth and Cornell additionally point out that most search and rescue operations are large enough to require complex sets of social and operational hierarchies, and they explicitly compare these hierarchies to the naval navigation teams described by Hutchins (1995). At the apex of the entire operation, search coordinators ultimately define the strategy for searching, often using non-spatial information about the target (e.g., a determination that the target was interested in photography, not fishing) to constrain the spatial search.

Thus far the consideration of search targets has been confined to targets whose quality (as targets) is binary—things that either are or are not what we are looking for. Early on, however, geographers also examined search as it relates to consumer behavior—searches for goods and services. In such cases, the quality of the target varies, and the termination of the search itself depends a great deal on issues of satisfaction (Golledge and Brown 1967). Searches of this kind also tend to be preferentially carried out in areas with which the searcher is already familiar (Cyert and March 1963). Hudson (1975) compared trade-offs between distance-of-travel and the reduction of uncertainty implicit in consumer types of searches involving recent migrants to an area, using shopping center size as a proxy variable that was inversely related to uncertainty. His results revealed that while distance overwhelmed uncertainty as a determinant in search behavior for individual shops, at the shopping center level the reverse was true. Apart from very interesting level-of-analysis concerns, these results suggest that the minimization of uncertainty partially explains search behavior, especially when paired with the observation of Cyert and March (1963) that searches tend to be preferentially concentrated in familiar areas.

Tellevik (1992) explored the hypothesis, based on the work of Fletcher (1980a; 1981b; 1981c), that systematic search strategies would improve learning of objects within a space. To this end, ten blindfolded sighted participants were asked to search a furnished room (6.2 × 5.2 m) for four objects. Participants completed the task twice, with the objects and furniture moved between trials. Tellevik recorded the frequency of gridline searches, perimeter searches, and reference-point usage, in which participants used an object or a wall to help fix the location of another object. At the end of the task, participants provided distance estimates via pairwise comparisons and built a model of the space. The results of his study revealed that strategy type changed markedly between trials. In the first trial, participants made extensive use of both perimeter and gridline searches, spending an average of 98% of their time using these kinds of searches, and only 2% of their time on reference-point use. This indicates that strong attention was given to the "find" portion of the task, and relatively less attention to the "remember" portion of the task. Overall search time in the second trial was nearly half that of the first trial but use of the reference-point strategy grew from about 2% in the first trial to 45.5% in the second trial. Interestingly, this dramatic shift did not result in any significant improvement of participants' knowledge about the locations of the objects in the room.

Hill et al. (1993) extended Tellevik's experiment to investigate strategies of visually impaired participants (rather than blindfolded sighted participants) who were asked to search a similarly sized space (4.6 × 4.6 meters) for four objects. The strategies were coded in the same manner as Tellevik, except that reference points were distinguished (object-to-object, object-to-wall, and object-to-start), and participants completed only one trial. Participants were evaluated on their learning of the spatial layout through several pointing tasks, for which an overall score of accuracy (mean absolute error) was recorded. These scores served as the basis to isolate the top (M = 17.3 degrees of absolute angular error) and bottom (M = 90.7 degrees) performing fifteen participants, out of an initial 65.

Good performers tended to report using and were observed using more strategies (both search and memorization-related) as a group than were poor performers, with the interesting exception that no one (good or poor) reported using a gridline search in post-task interviews, though such searches were actually conducted. Good performers tended to complete the task in less time, and also tended to use more reference point visits of every type. Gridline searches were relatively rare for both good (30%) and bad (10%) performers, but the latter used perimeter searches nearly twice as often as good performers, though they verbally reported using fewer. This result supports Pingel's (2012) claim that the ability to externalize one's strategy is an important element of a strategic disposition in that it demonstrates a more complete awareness of one's strategy.

A second extension of the Tellevik (1992) experiment focused on the differentiation of object-linking memorization strategies. Gaunet and Thinus-Blanc (1996) found that blindfolded sighted participants tended to use "back-and-forth" object-linking strategies (a series of sequential visits between the same pair of objects), while early blind participants were likely to use cycles of visits, where each of the four objects was visited sequentially. These cycles of visits led to poorer overall spatial layout learning when compared to participants that used back-and-forth object links. Importantly, Gaunet and Thinus-Blanc demonstrated that neither performance nor selection of strategy type was linked to a measurement of participant IQ.

Many types of wayfinding experiments in general, and search experiments in particular (e.g., Ruddle, Payne, and Jones 1999) have been conducted in virtual spaces. While many of these glimpses into spatial cognition generalize well to non-virtual contexts, scale is a particularly difficult concept to model in a virtual environment, since this conflates real world figural spaces—tabletop, manipulable spaces smaller than the body—with larger scale spaces. In addition to figural space, Montello (1993) distinguishes between three other scales of spaces: vista, environmental, and geographical, divided largely based on the degree to which locomotion is a factor in learning the space, and whether the space is larger or smaller than the body. Used in this way, scale acts as a function of *extent* or *size*. Vista scale spaces are those in which the space may be apprehended from a single location, without appreciable locomotion, and would include both room-sized spaces as well as larger spaces like campus greens or town squares. Interaction with virtual spaces, either through a desktop or via a fully immersive virtual environment, will nearly always blur the lines between the experienced and represented scales (Pingel and Clarke 2012; Waller, Hunt, and Knapp 1998). The construction of psychologically-based categories of scale rests on the notion that individuals' thinking and behavior in different kinds of spaces will be more alike within groups than between them, and Montello (1993) offers evidence to this effect. We offer evidence, via a controlled experiment, that shows that search behavior within vista sized spaces is highly variable, thereby suggesting a refinement of Montello's taxonomy may be necessary.

METHODS

The experimental setup was inspired by the work of Tellevik (1992), Hill et al. (1993), and Gaunet and Thinus-Blanc (1996) in which participants were asked to find and remember the locations of four objects in a vista-scale (Montello 1993) space. However, unlike these experiments, participants searched in one of three possible scale conditions: (1) an indoor (small) space, measuring 4.6 × 4.6 meters (area: 23.3 m^2); (2) an outdoor (medium) space, measuring 13.8 × 18.7 meters (area: 258.0 m^2); or (3) an outdoor (large) space, measuring 23.1 × 43.0 meters (area: 993.3 m^2). Here, scale refers to the extent or absolute size of the space.

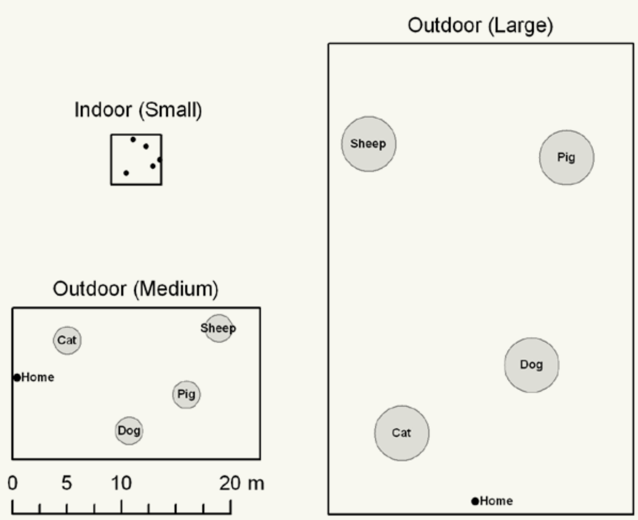

Figure 1: Comparison of sizes and trigger areas for search sites.

	small	medium	large
dimensions (m)	4.6 × 4.6	18.7 × 13.8	43 × 23.1
area (m2)	20.9	258.8	993.6
trigger diameter (m)	0.6 – 1.0 (est.)	2.5	5.0
trigger area (m2)	.46 (est.)	4.9	19.6
trigger ratio (A/TA)	45.8	52.7	50.6

Table 1: Comparison of sizes and trigger areas for search sites.

In addition, rather than searching for physical objects, participants in our experiment searched for *invisible objects*: locations in the space marked with audio cues. That is, when a participant walked within range of four defined trigger areas, they would hear the sound marking that particular location. In this way, participants could use vision to coordinate locomotion and search, but not to locate objects. Details about the search spaces and the arrangement and sizes of trigger spaces are shown in Table 1 and Figure 1.

PARTICIPANTS

Forty-eight individuals participated in the experiment; all were drawn from introductory geography courses and participated in exchange for extra credit. Twenty-one of these were male, and the mean age was 20.8 (SD = 3.9). Fourteen participants searched the small space, 16 searched the medium space, and 18 searched the large space, and the ratio of males to females was approximately equal in all conditions. No participants reported any hearing impairment that would preclude participation in the study, and all were able to respond appropriately to speech and sample audio cues. Written informed consent was obtained according to the provisions set by the University of California, Santa Barbara (UCSB) local institutional boards.

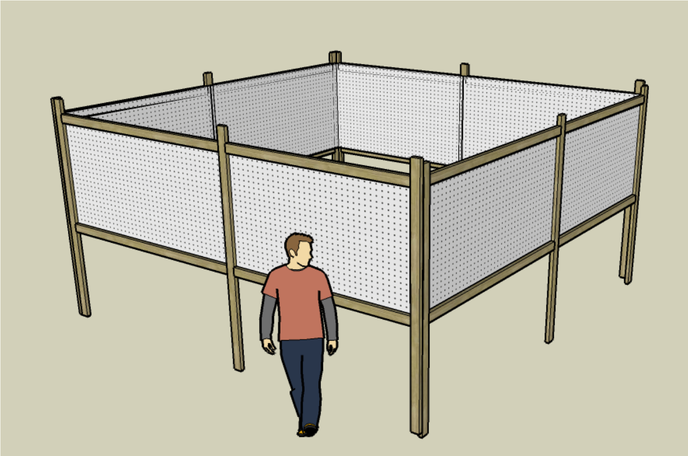

Figure 2: Diagram of the indoor search space.

MATERIALS

The small search space was constructed from a wooden frame and several pieces of thick pegboard (Figure 2). There were no obstacles in the room. The room was housed in a large human geography laboratory on the UCSB campus.

Audio cues alone marked the location of each of four "objects" that each participant attempted to find. The sound cues for each object location were transmitted to the participant via a pair of Bluetooth wireless headphones. The location of each participant was tracked through thirty, low-power (<1 milliwatt) red lasers and paired photoreceptors. Fifteen lasers were placed on two adjacent walls, and paired with photoreceptors on the opposing two walls. This configuration allowed us to capture the participants' spatial location in two dimensions with a spatial resolution of one foot and a temporal resolution of one tenth of a second. Laser arrays and photoreceptors were placed at the bottom of the pegboard (1.1 m from the ground).

Variance in the resistances from the photoreceptors was monitored with a keyboard encoder (model: KeyWiz Eco). As light beams were interrupted by a participant's body, resistances in the photoreceptors dropped to zero, which the keyboard encoder then relayed to a PC as simulated keystrokes. Java software, written by the authors, monitored the virtual key states and handled a visual display, recorded a log of the participants' locations, and transmitted one of four sounds corresponding to the four object locations in the room. These audio cues were approximately one second in length, and were continuously played (looped) as long as the participant remained at the location. The sounds used were that of a dog barking, a cat meowing, a sheep bleating, and a rooster crowing, and all were within frequencies used for everyday speech. These sounds identified the locations so that each location, or "invisible object", was referred to throughout the experiment by the animal name associated with the sound (e.g., "Where was the cat?").

The medium and large spaces were sectioned off portions of the UCSB campus. The medium-sized space was a large, grassy area slightly elevated above the surrounding walkway. The large-sized space was a portion of a campus green, separated from the surrounding green by identical landmarks (flagged wooden dowels) on each corner. Tracking of user position in the outdoor spaces required a high-precision GPS unit; we used a Trimble AgGPS 114 model, designed for use in precision agriculture. In a thirty-eight hour field-test conducted by the authors, the root mean squared error (RMSE) for absolute distance deviation of the unit from the average was 0.55 meters. Ninety-five percent of all observations had an error less than 1.02 meters. This unit was used with excellent results in a navigation system for the blind (Loomis et al., 2005). By way of comparison, in a similar trial conducted by the authors, a consumer-grade GPS unit utilizing the MTK GPS chipset produced a GPS log with an RMSE of 1.6 meters, with 95% of all observations less than 2.7 meters from the mean. The Trimble AgGPS 114 unit used in the study was configured to output its position five times per second over serial cable to a laptop computer. Both the laptop and GPS unit were attached to a metal backpacking frame, and the complete weight of the backpack was approximately five pounds.

A computer program was written in Java to read position information from the device, convert the position to Universal Transverse Mercator (UTM) coordinates, and log the position and other context information related to the quality of fix (e.g., number of satellites used, dilution of precision values, and differential correction availability) to a file on the local disk. The software was also responsible for interpreting whether the participant was near enough to a waypoint to play the corresponding audio cue from the PC speaker. The position of the participant was logged to hard disk once per second.

The sizes of trigger sites were scaled to be proportionally equivalent between conditions. In the small search space, the interruption of two designated (x and y) lasers triggered the audio cue. In practice, the perceived size of this trigger was related to body size. Pilot testing placed the perceived trigger radius at approximately 0.46 meters. This value was used to scale the trigger area so that it would be proportionally equivalent at the larger spaces, and was set at 4.9 m^2 and 19.6 m^2 for the medium and large sized spaces, respectively. This resulted in a trigger area to total area for each object of approximately 1:50 at all scales. The spatial distribution of the trigger sites was designed to mirror, as closely as possible, the distribution used by Hill et al. (1993). In this way, although the size of the space increased, the arrangement of the trigger sites remained constant across conditions.

Following the task, participants indicated their estimates of the positions using a tripod-mounted digital compass (model: Coleman Digital Compass 814-672T). Additionally, participants in the small search space condition completed a post-task debriefing. The results of that briefing informed the development of a 5-item questionnaire used to calculate a strategic disposition index (SDI) that corresponds to the degree to which a person actively strategizes when wayfinding (Pingel 2012). Participants in these conditions additionally completed the 15-item Santa Barbara Sense of Direction Scale (SBSOD) questionnaire, shown to correlate well with overall environmental spatial ability (Hegarty et al., 2002). The SBSOD represents a mechanism to measure participants' self-assessment of their own sense of direction, and therefore a way to partially separate strategy from general performance on environmental spatial tasks.

PROCEDURE

Upon arrival for the study, participants indicated consent to participate and were read task instructions by the researcher. The key instruction for participants required them to "find and remember the locations of four invisible objects in the room, whose positions [were] marked with audio cues of animal sounds." They were then taken to a common start location ("Home") and instructed to indicate to the researcher when they felt they knew where the "animals" were. At this point, the researcher entered the space with the tripod-mounted compass, asked the participant to return to the start location, where participants were asked to point to the animals. The order was dictated by the researcher, and was chosen at random for each participant. Finally, participants completed both the SDI and SBSOD questionnaires, and indicated their age and sex.

DATA PROCESSING

The digital log produced by the Java software written for the small search space recorded the time, activity of each laser sensor (binary on or off), and the sound (if any) that was playing at that moment in a comma delimited text file, with ten records logged each second. The position of the participant was determined by taking the average of the activated sensors for each line entry in the log. For the outdoor space, GPS position and trigger activation was logged once per second. In all cases, any missing values were linearly interpolated. These logs provided a record of total time and total distance travelled.

To segment the data more meaningfully, we approached the problem in two ways: (1) we segmented the tracks according to the likely goal to which movement was directed, and (2) we classified the overall type of systematic search by the participant, if any. Since the task required participants to both find and remember the locations of objects—two conceptually distinct directives—we developed an automated algorithm to classify each segment of a participant's track into one of three types of movement: search, localization, and reinforcement. *Search* applied to track segments in which the participant had goal directed movement to an object not previously found. *Localization* applied to track segments in which the participant attempted to finely fix the location of the object in the space through repeated sequential movements to the same trigger site. *Reinforcement* corresponded to track segments in which the participant returned to a previously found object, and coincides with Tellevik's (1992) "reference-point" strategy and Hill et al.'s (1993) "object-to-object" strategy.

Visits to objects were recorded directly by the logging software based on the initiation of the audio cue. Localization was distinguished by the observation of repeated movement to the same object within a specified amount of time (5 seconds), and reinforcement was defined by movement to a previously found object within a specified distance proportional to the mean distance between objects for that sized space. If the participant had previously found all four objects, any subsequent movement between objects (i.e., movement not classified as localization) was also classified as reinforcement. Any movement not classified by the above criteria was classified as search. Movement between two previously found objects could therefore be either classified as search or reinforcement, depending on how direct the movement was. Most reinforcement movement was of the kind shown in Figure 3c: manifestly direct, and therefore short returns. Indirect movement between previously found objects (e.g., some legs in the gridline search shown in Figure 3b) could have been classified as search if the distance between objects was excessively lengthy. This, however, was not an incorrect interpretation in most cases given that the algorithm correctly interpreted the longer return visit (a function of a visit to the edge of the space) as the result of search rather than reinforcement behavior. Animations from the output of the classification were used to iteratively refine the algorithm based on visual inspection. This method was less likely prone to human error and allowed for a more objective and easily repeatable type of classification.

Three external judges were asked to examine the final animations and to code for presence/absence of two different search strategies: (1) a perimeter search, defined as "a systematic search of the outside edge of the space, consisting of at least three consecutive edges/walls," and (2) a gridline search, defined as "a systematic search consisting of a series of parallel transects covering all or part of the space." Fleiss's kappa, which indicates level of agreement, and ranges from -1 (perfect disagreement) to 1 (perfect agreement) was 0.88 for perimeter coding among the three judges, and 0.83 for gridline coding. A participant was ultimately coded as having a perimeter or gridline search present if two of three judges agreed. Examples of the tracks of four participants are shown in Figure 3.

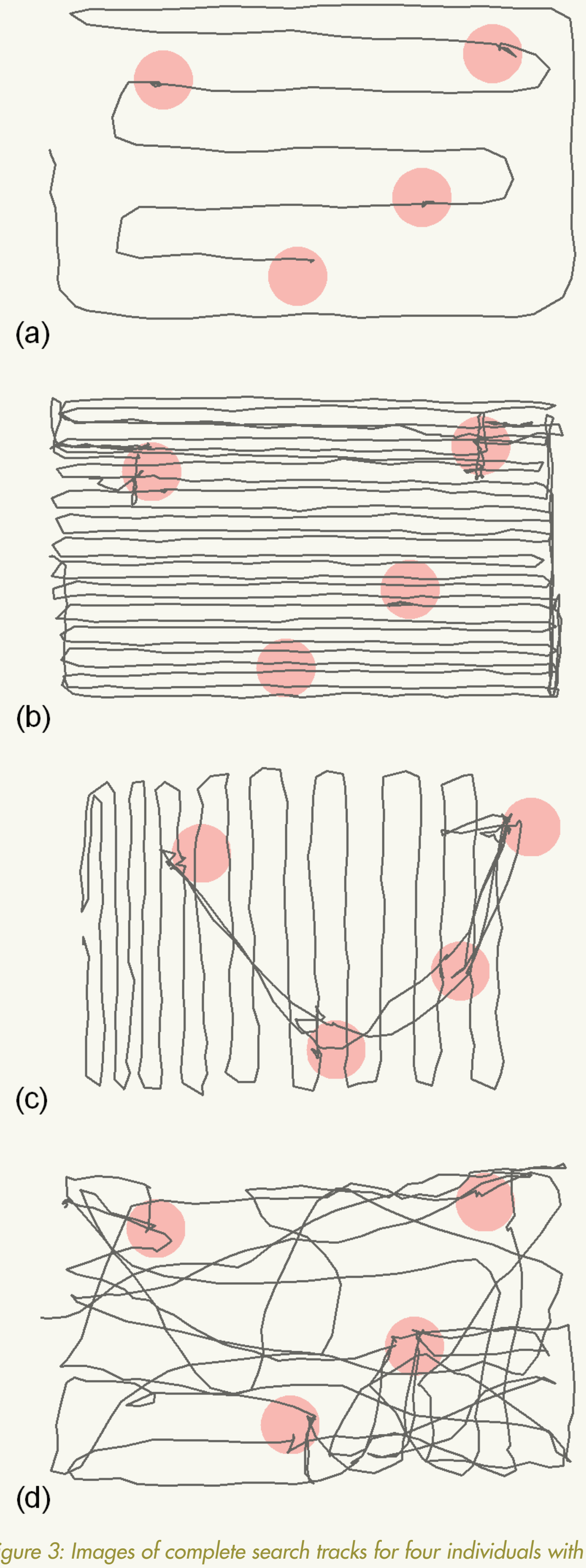

Figure 3: Images of complete search tracks for four individuals with trigger sites shaded. Figures 3a to 3c show evidence of systematic, gridline searching, while Figure 3d does not.

RESULTS

Given the difference in tracking technology between indoor and outdoor conditions, we felt it important to apply some simple diagnostics to the dataset to ensure measures of behavior and performance met expectations. As one would expect, mean total track length increased monotonically with scale, with a Pearson's correlation of $r\,(46) = 0.47$, $p < 0.001$. This was not the case with total time travelled, as participants in the large-scale condition moved much faster ($M = 0.94$ m/s, $SD = 0.16$) than did participants in either the small ($M = 0.60$, $SD = 0.10$) or medium-scale conditions ($M = 0.64$, $SD = 0.12$). The difference in speed was significant according to a general linear regression model using the square root of the area as the predictor, unstandardized $\beta = 0.01$, $t\,(46) = 7.34$, $p < 0.001$. As a result, all further analysis is presented in terms

	small	medium	large
total distance (m)	143.5 (61.4)	203.9 (96.9)	267.8 (120.8)
total time (s)	240.4 (96.9)	319.8 (148.5)	286.6 (129.3)
mean speed (m/s)	0.60 (0.10)	0.64 (0.12)	0.94 (0.16)
gridline searches (%)	21.5	56.2	66.7
perimeter searches (%)	85.7	12.5	16.7
search distance (%)	52.5 (23.3)	67.7 (16.6)	77.4 (16.4)
localization distance (%)	11.2 (8.1)	15.2 (6.9)	14.3 (7.0)
reinforcement distance (%)	36.3 (19.1)	17.2 (13.5)	8.3 (14.5)
search distance (m)	68.0 (35.2)	141.7 (77.7)	200.9 (88.5)
localization distance (m)	18.0 (16.3)	27.9 (11.6)	35.3 (16.0)
reinforcement distance (m)	57.6 (41.2)	34.3 (28.4)	31.6 (62.1)
mean absolute pointing error	24.8 (18.55)	10.1 (6.5)	9.9 (3.8)

Table 2: Results (mean and standard deviation) by size condition. Larger spaces featured more gridline searches, and participants tended to spend more time searching for and less time reinforcing knowledge of the locations of objects as the size of the space increased.

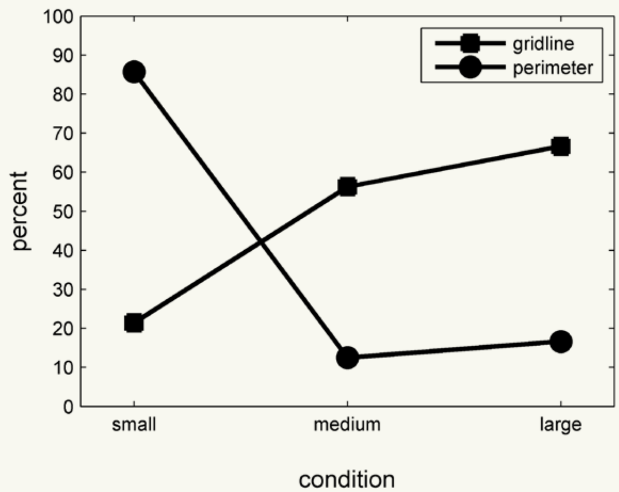

Figure 4: Perimeter searches were common in the small search space, but much rarer in the larger space. Gridline search rates increased monotonically with the size of the search condition.

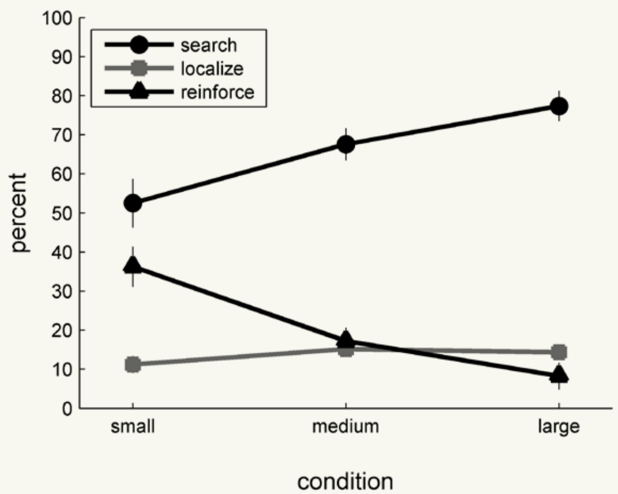

Figure 5: Mean distance as a percentage of overall track length spent on search increased with increasing size of the space, while mean distance (%) spent on reinforcement decreased. Localization showed a moderate, statistically insignificant increase.

of distance, rather than time. Complete descriptive statistics by scale condition are presented in Table 2.

Mean absolute pointing error diminished monotonically as the size of the search space increased. Mean error was 24.8 degrees at the smallest scale, 10.1 degrees at the medium scale, and 9.9 degrees at the largest scale. These differences were statistically significant, $\beta = -0.50$, $t\,(46) = 3.31$, $p < 0.002$.

Scale proved to have a strong impact on the type of search strategy that participants used. The propensity to search using a gridline strategy increased as the size of the space increased: in the small space, 21.5% of individuals used a gridline search, but the rate increased to 56.2% for the medium-sized space, and 66.7% for the large-sized space (Figure 4). The difference was significant according to logistic regression where a binary value (0 = no gridline; 1 = gridline) was used as the dependent variable, and the square root of the area was used as the predictor ($\beta = 0.07$, $t\,(46) = 2.34$, $p = 0.02$). Perimeter searches showed the inverse pattern, as small-sized spaces were more likely to be searched via perimeter and large-sized spaces were less likely to be searched in this way (β = -0.12, $t(46) = 3.19$, $p = 0.001$).

In addition to influencing how individuals searched, scale played an important role in the composition of wayfinding (i.e., the amount of distance participants spent *searching*, *localizing*, or *reinforcing*) during the task (Figure 5). While the percent of distance spent *localizing* remained largely unchanged, participants spent more distance *searching* and less distance *reinforcing* as the size of space increased. Search percentage was 52.5% in the small space, but increased to 67.7% in the medium-sized space, and 77.4% in the largest space; a similar decrease was noted for reinforcement behavior (see Table 2). Linear regression indicated the relationship was statistically significant for both search (β = 0.90, $t\ (46) = 3.67$, $p < 0.001$) and reinforcement (β = -1.00, $t\ (46) = 4.7$, $p < 0.001$).

The addition of sex to the preceding regression models did not significantly improve predictive performance, indicating that there were no detectable sex differences in these strategic measures. Similarly, although there were differences observed between conditions for mean absolute pointing error (β = -0.50, $t\ (46) = 3.31$, $p = 0.002$), sex differences were not significant when added to the model (β = -4.70, $t\ (45) = 1.42$, $p = 0.16$).

Correlations between SBSOD score (a self-report measure of environmental spatial ability, Hegarty et al. 2002) and SDI score (a self-report measure of strategic disposition in wayfinding contexts, Pingel 2012) did not reach statistical significance. However, while correlations between SBSOD and search type were positive ($r = 0.06$ for gridline, 0.05 for perimeter search), correlations between SDI and search type were negative ($r = -0.12$ for gridline, -0.05 for perimeter search) indicating that self-described strategists were less likely to use systematic search.

An explanation for these results may rest with the overall lack of improved performance between systematic searchers and non-systematic searchers. Gridline searchers did not significantly improve mean absolute pointing error (β = -3.80, $t\ (45) = 1.08$, $p = 0.029$) although the beta coefficient was in the expected direction (Hill et al. 1993). More importantly, gridline searching did not reduce overall search distance (total distance × search percentage). Regression analysis confirms that gridline searchers actually spent *more* distance searching than non-gridline searchers in a model that included presence / absence of gridline search and the square root of the area of the space as independent variables (gridline β = 46.9, $t\ (45) = 4.19$, $p = 0.03$; Figure 6). Mean search distance was longer for gridline searchers, but variability was slightly lower in the small and medium-sized spaces and slightly higher in the large-sized space (Figure 7). This provides some evidence that systematic searching may be an attempt to limit the variability of the result rather than to reduce the mean distance travelled.

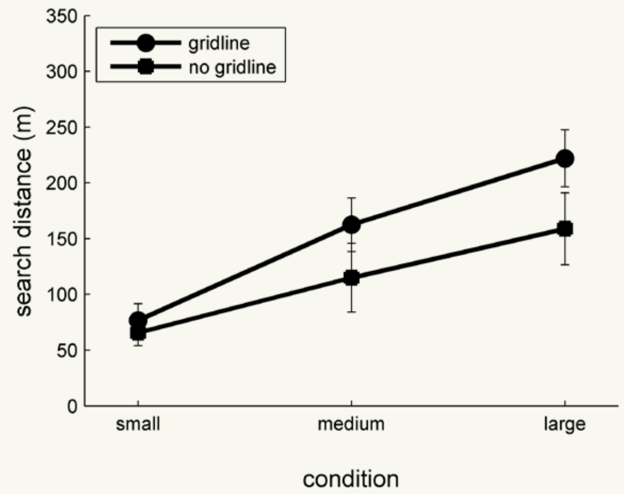

Figure 6: Mean search distance for gridline searchers was longer than non-gridline searchers for all conditions.

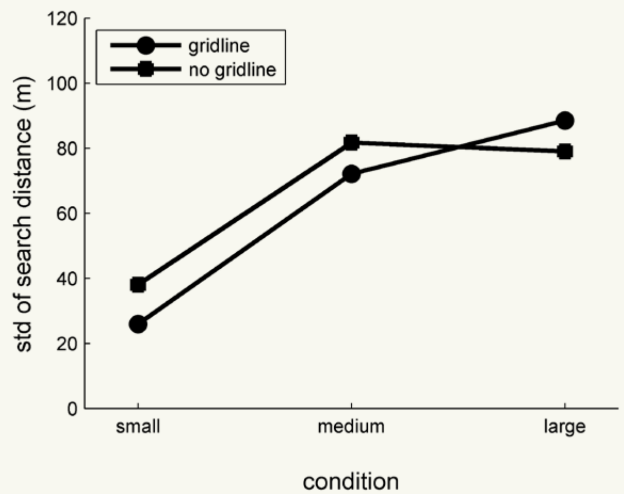

Figure 7: In small and medium-sized spaces, but not large spaces, gridline searchers had reduced variability in search distance.

DISCUSSION

The experiment detailed above extended previous studies on search strategy made by Tellevik (1992), Hill et al. (1993), and Gaunet and Thinus-Blanc (1996). In this case, however, searches were conducted by non-blindfolded, sighted participants who looked for "invisible" objects in spaces approximately 25 m^2, 250 m^2, and 1,000 m^2. Participants in the small space condition showed search pattern distributions somewhat similar to Tellevik, in that perimeter searches were more common than gridline searches. Gridline searchers in particular were notably higher than Hill et al.'s (1993) best performers. We submit that the difference in gridline search rates observed between our study and Hill et al.'s stems from the ease with which vision enables the searcher to coordinate their search in space (Thinus-Blanc and Gaunet 1997).

Our results generally contradict Tellevik's explanation that the drop in systematic search behavior between successive trials that he observed can be attributed to a familiarity with the space on the second encounter. Were this true, one would expect sighted individuals in similar circumstances to rarely use perimeter or gridline searches. In our experiment, in an equivalently-sized space, perimeter searches were very common, and gridline searches were hardly rare. Since our participants could apprehend the space immediately with vision, these systematic searches had no impact on learning the configuration of the space. A more likely explanation of Tellevik's results is that participants shifted their focus from *finding* to *remembering* the locations of the objects.

A similarly important finding is that the type of search is a poor predictor of either pointing performance or search distance. A more useful predictor was the amount of distance spent on *reinforcement* rather than *searching* during the task—a value that corresponds with Tellevik's *reference-point* strategy, or Hill et al.'s *object-to-object* strategy. In effect, the searcher must choose the degree to which they focus on the "find" versus the "remember the locations of" instruction, while at the same time reducing the total amount of time, distance, or effort spent on the task. Just as in the well-described speed-accuracy tradeoff observed in other types of psychological testing, the searcher attempts to balance many criteria to their own satisfaction.

In this sense, strategy is neither equivalent to performance, nor to systematic search. In this study, participants who used the most systematic of searches we coded for—the gridline search—took longer to search the space than those who did not. This counterintuitive result indicates that the drive for systematization is not necessarily about improving the overall mean result, but is related to some other factor—perhaps aspects of personality or risk aversion. This perspective is in accord with the observation that SDI score—a self-report measure of strategic disposition—was not a significant predictor of search strategy. SDI speaks to the degree to which a person conditionally reasons about the impact of their behavior on variables that affect the achievement of desired ends, but says nothing about the particular plans or methods that the strategist might use. In many strategic games, an introduced degree of randomness can be a better strategy than an entirely systematic one, and famous strategists have differed quite markedly in the degree of planning and orientation to risk inherent in their strategies.

Reducing the mean (or median) cost of the search is clearly important to the searcher. The systematic ways that have been devised to conduct a search largely focus on segmentation (dividing the work into manageable pieces) and the prevention of overly-redundant effort. A gridline or parallel search is useful, in large part, because it is a simple pattern that prevents the space from being searched unevenly. As important, though, is the variability of cost measure enabled by a systematic search. Systematic search may well reduce the mean cost, but it also makes the cost more predictable. In searches where lives are at stake, the reduction of variance may be paramount, for the searchers may not care so much what the mean solution time is as much as they care that it likely does not exceed a given value. While central tendency and dispersion often vary together for these types of costs, it is helpful to recognize that the uncertainty associated with large variability is often considered a cost of its own, and as such its reduction is a direct target of strategic behavior.

Finally, as the size of the space became larger, participants increasingly focused on search rather than reinforcement. The shape of the curve describing the change (Figure 5) is also curvilinear, suggesting that—as Tobler (1993) observed in a different sort of transportation problem—the cost of overcoming distance increases, but at a decreasing rate. At larger sizes of space, travel costs are perceived as higher to the degree that observed behavior changes qualitatively. Since all searches took place at the vista psychological category of scale—a size of space that Montello (1993) described as being capable of apprehension without appreciable locomotion—this suggests that kinds of spaces may have finer gradations than are commonly appreciated. In particular, it suggests that the costs of traversing room-sized spaces are qualitatively different than the costs of traversing town-square, or campus green-sized spaces.

One limitation of the study was its somewhat small sample size. In our case, the effect size of scale on strategic variables was large enough such that significant differences were apparent between conditions. However, we did not detect significant differences for sex, environmental spatial ability, and strategic disposition in some cases in which they might have been expected. As a result, we can only comment that there were no observable differences for these variables, and hope that our results may provide better upper bound estimates for effect sizes in future work on this topic.

A second limitation of the study involved the control of landmarks between conditions. The small space was relatively featureless, while in the outdoor spaces, participants had a full view of surrounding landmarks. This was unavoidable given the infeasibility of constructing such a large, featureless space, and blindfolds would have artificially limited the ability of participants to coordinate a search. In any case, post-task debriefing of participants in the indoor space condition revealed that they had no difficulty constructing landmarks from otherwise trivial imperfections (e.g., a scratch on the floor) or in maintaining orientation within the room. For this reason, we believe it unlikely that differences in landmark availability significantly influenced the results.

CONCLUSIONS

In search-based wayfinding problems, the size or extent of the space to be searched has a profound effect on the types of strategies used to explore the space. In this experiment, in which participants were asked to find and remember the location of four positions in an empty space marked only with audio cues, small (~ 20m^2) sized spaces elicited relatively less systematic, more random spatial searches and relatively more effort spent on reinforcing the relative positions of objects via repeated object-to-object visits. Participants searching larger spaces (~250 m^2 and ~1000 m^2) rarely used object-to-object visits, but much more frequently used gridline search patterns to explore the space.

Since search is an integral part of wayfinding, whether by navigating to a previously unknown destination or through evaluating potential routes between waypoints, understanding how scale can impact the strategies that individuals use is a key requirement. Our results suggest that wayfinding preferences commonly integrated into navigation software should be designed with scale in mind. For instance, a preference for simplest paths—where absolute performance in terms of time or distance is sacrificed in order to reduce the complexity of the route—may be more applicable at smaller spatial extents than larger ones. This is because at smaller scales, small sacrifices of time or distance may be discounted, while at larger scales, the costs of traversing space may be viewed as relatively higher.

Finally, these results suggest that while different scales of spatial problems—figural, vista, environmental, and geographical—may indeed elicit different kinds of thinking, the categories themselves are somewhat flexible. Our results indicate that individuals strategize about room scale spaces very differently than campus-green or town-square sized spaces, and yet both of these exist at the vista scale. While it is possible that differences in indoor vs. outdoor administration of the experiment caused the differences, even this would require some amendment to Montello's (1993) categorization of the psychology of scale. Ultimately, a multidimensional taxonomy of the kinds of the changes in the quality of spatial thinking we find at different scales may prove the most useful in delineating the most appropriate divisions of a psychology of scale.

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