Which Strategy for Way-finding? – A Computational Evaluation

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Abstract. We compare three well-established strategies propsoed for human multi-location way-finding in regionalized environments: a) *fine-to-coarse*, b) *cluster*, and c) *least-decision-load* [1]. First, we attempt to construct an operationalizable model for these strategies on a subjective basis, based on a cognitive graph generated using ordered tree algorithm by [2]. We conduct two experiments on the same set of subjects, first to assess their hierarchical map structures for a familiar area, and then to consider how their actual wayfinding behaviour manifests. Their behaviour is then compared with a computational simulation based on differing combinations of the three strategies. Results indicate that the previous assumption of equi-probability for these three strategies may not hold, and that behaviour of the respondents appears to be dominated by the *fine-to-coarse* strategy. The simulation approach can also be used to analyze interfaces for aiding human way-finding and other applications.

Keywords: Computational Model, wayfinding, hierarchical representation, regionalized environment, papameter estimation

1 Introduction

Cognitive mechanisms for navigation and wayfinding have attracted considerable attention over several decades [3, 4, 1]. Wayfinding is related to well-studied algorithmic problems such as human capabilities in solving the travelling salesman problem [4, 5], but differs in two important aspects. First, the entire space is not available visually, so that memory constraints come into play. Also, the large spaces involved call for granularity at different scales, and both representations and operations on these are considerably different [6]. Since navigating paths in large-scale familiar spaces is what humans do many tims every day, mechanisms for such capability are of great interest. Cognitive representations and planning strategies for wayfinding have been investigated by mechanisms such as sketching [7], ordering of sites based on recall [8], navigation paths on

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virtual scenes [1], linguistic interactions [9, 10], as well as brain FMRI studies [11].

As a result of these approaches to investigate wayfinding, a number of strategies have been proposed to explain human navigation abilities [9, 10, 1]. These strategies are essentially heuristics that are not mandated by the task but appear to help in minimizing the computations or improving the effectiveness of the path. Whether such strategies are learned or part of our native inheritance remains to be investigated. The specific strategies proposed include the *fine-to-coarse* strategy [12], where one simultaneously uses fine-space information for locations within a region and coarse-space information for distant locations. This is based on a *focal representation*, which represents near-by places, i.e. the places in the same region, in full detail whereas places in other regions are represented by the entire region at the time the decision is made, leading to reduced cognitive effort. [1] has combined this approach with two older proposals which are also used on certain occasions: (i) *cluster* method, first described by [13], which asserts that one tends to first visit the region with highest concentration of target places, and (ii) *least decision load* [14], which says that one prefers a path which amounts to the least number of decisions taken, which also results in the largest distances towards the goal being traversed at once. Another approach, the *least-angle strategy* [10], proposes that the human deviates as little as possible from the angle of the path, but admits a number of corrective measures. A number of other strategies apply to unfamiliar domains, and are not considered here ([15]), where we restrict ourselves to well-familiarized spaces.

Other proposals, such as one involving complex multi-level planning strategy [7] based on the hierarchical map has not been collaborated by other data [9]. A number of other strategies have been reported in specialized domains. For example, Parisian taxidrivers appear to use a familiar *primary network* of main streets to order their navigation. For the purposes of this paper, we consider a less heterogeneous street configuration (a campus area) where most of the respondents travel by bicycle or by foot, and differences between streets are not as significant. Also, several of the earlier approaches, based on similarity, are merged into one of the three primary strategies proposed by Wiener and Mallot [1]. For example, the least-angle strategy is seen to be sufficiently similar to the least-decision load strategy. Thus, we limit ourselves to the three strategies of fine-to-coarse, cluster, and least-decision load. These three strategies have also been used as the basis for a number of other evaluations [9, 6], and appear to have gained considerable acceptability as cognitive approaches for planning routes in a regionalized environment.

In earlier work, it has been thought that some combination of these strategies are used in wayfinding. Thus, different segments of a path may call for differeing strategies. It was felt that each strategy is more or less equally likely in these situations, and no study on the relative preponderance of these strategies have been considered. For example [1] leaves this question unanswered, though they suggest that human navigation behaviour may be a linear combination of these three heuristics with equal weights. Our present computational model, through the use of a dynamic system and actual experiment on subjects, tries to validate the applicability and importance of the three methods.

The two questions we ask in this work are: a) whether these three strategies sufficiently explain the user response, and b) what frequency may be observed for the deployment of various strategies? In order to answer such questions, we need to model the responses of each strategy in a given situation. For this purpose, we need to construct a operational model that can be implemented in computational simulation.

While a number of theories have been proposed for human wayfinding strategies, there are few computational models that simulate such behaviour. Many computational studies have adopted a path-cost minimization strategy [16, 17]. Another computational approach, the Traveller, adopts the hypothesis that one goes first to the centroid of the present region, then from there to the centroid of the target region and thence to the target, completing the navigation process in three stages [18]. However, the model is not realistic for cognitive way-finding since for start points close to the region boundary of the target region, a subject would rather prefer to cross into the target region than to go to the centroid of the starting region first. Another computational investigation [19] propose a model that considers a *coarse-to-fine* heuristic, according to which we first generate a coarse route plan using higher abstraction levels. However, this heuristic has been shown to lead to contradictory results [1]. As such, there is hardly any computational model to supplement statistical works in this area and our present work is a step towards that direction.

A number of other computational studies have attempted to model the neural processes involved in rodent navigation. Thus, [20] uses *locale* and *taxon* strategies and associates them with representive parts in the brain for navigation in rats. [21] presents a Computational Model of Cortico-Basal-GangliaThalamo-Cortical Loops for integration of navigation and action selection functionalities. [22] employs two different navigation strategies (a *cue-guided* and a *map-based* one) to explain rodent behaviour. However, these are not directly related to our domain, since it is not possible to obtain any guidelines on the spatial representation for individual rodent subjects.

In the context of human wayfinding, a serious challenge for operationalizing the qualitative suggestions implicit in these strategies is that is that the system must also have an internal representation for the space. In this work, we adopt the ordered-tree approach [2] as implemented in the system TIGER [23]. Note that this representation is subjective, so that it may differ considerably from user to user, based on their personal history of spatial experiences, personal biases, as well as aspects of the geographic area. Based on this, we then implement each of the three strategies and adapt a randomized winner-take-all decision making for each sub-path. Two parameters, α and β determine the probabilities of choosing fine-to-coarse and cluster strategies, while $1-\alpha-\beta$ is the probability of the *least-decision-load* strategy. We then present a validation of our model by conducting experiments in local way-finding and comparing the actual human behaviour with a computational implementation based on our model. Note that owing to the subjective nature of the cognitive map, the validation experiment will require two phases of interaction with each user, one to construct their subjective cognitive maps, and a second to obtain their responses to various sequencing tasks.

We next consider the model of spatial representation, leading to the construction of a subjective map for each user.

1.1 Spatial representation

Wayfinding strategies must necessarily work on some kind of mental representation of the space. For familiar large scale spaces as being considered in this work, there is abundant evidence that such spaces are represented in spatial memory not as a single-level map, but as a hierarchy with nested levels of details ([24, 8]). The hierarchical model of spatial memory suggests that space is organised into a graph-like representation based on personal biases and spatial characteristics. Such a model has been argued for based on errors of distance and direction [25], as well as based on limitations of working memory [24]. The structure of such hierarchical cognitive representations have been investigated by Hirtle and Jonides [8], who evaluate spatial clusters with reference to a natural environment of a campus, basing their work on the ordered tree algorithm proposed by [2] on recall protocols to arrange 32 places inside the campus into individual hierarchical clustering. Distance estimation tasks on the subjects revealed that they underestimated distance between places in the same cluster while for the places in different clusters, the distance was overestimated.

So, through this work we (i) first propose an operationalizable dynamic model for the three strategies in [1] based on a cognitive graph generated using an ordered tree algorithm, and (ii) conduct experiments in local way-finding and compare the actual human behaviour with a computational implementation based on our model, so as to decide upon the relative importance of the three heuristics in a regionalized environment like IIT Kanpur campus.

2 Computational Model

The model we propose uses the IITK campus as the natural familiar region. A map of the campus with the concerned places is shown in Figure 1. In subsequent subsections, we describe the methods to first organize the campus into regions, representing each region with a representative point, finding weights to decide on the strategy, and finally comparing the outcome with experimental data.

2.1 Representation of the Regions

As has been previously ascertained, human spatial memory is hierarchical in nature and as such, it is more sensible to arrange the campus in a hierarchical graph rather than a spatial map. Graphs are always advantageous over maps as, (i) they are much more flexible compared to maps: though they are topological structures, information about distance and direction can be easily incorporated through weights according to which the edges will be defined; (ii) the set of movements available at a particular place can be clearly and unambiguously represented; (iii) emotional and other non-physical factors can be accounted for by assigning proper weights to the edges; (iv)incomplete or inconsistent information can be readily incorporated without serious implications for the whole topology. To quote [12], "graph-like representations of space are both, ecologically sensible (i.e., minimalistic) and sufficient." The use of graphs for cognitive models and AI models can be seen in [26, 19, 27]. In fact, [28] presents a detailed account of graph-based models of space in cognitive science. Drawing from the above, to faithfully represent the spatial memory organisation and keeping our particular objective in mind, we followed the following approach: each place/landmark is represented by a node. The region that encompasses this particular landmark is represented as a parent of this node, called a 'super-node. Each super-node contains the places inside it as its children. In addition to that, a representative of every other super-node is also a child of the present super-node, so that distant regions are represented as a single point from the present perspective. The children of a particular node are connected in a way that reflects the actual topological distribution, so that only directly accessible places are connected to each other and the node representing distant region is connected only to the place in the present region that is physically connected to it, or to the region that acts as a bridge between them.

One of the challenging parts is to divide the campus into regions. As [29] asserts, region boundaries are very vague. Sometimes, the regions overlap too. Furthermore, every single person has a representation that differs from the next one, based on personal biases. As such, a model that uses the same region representation for every individual is prone to errors. We, therefore, settled on creating a region based representation for each test subject through the use of the ordered tree technique (OTT) proposed by [2]. The OTT was first proposed to assess the underlying organization in memory. [8] used it to divide Ann Arbor campus into individual regionalized representation and support the hierarchical nature of spatial memory, as has been described before. We followed a similar approach, and used [30]'s technique, which is essentially an adaptation of the OTT that reduces the required effort and time. For a detailed description of the original technique and its viability, we direct the reader to [8, 2]. We followed this approach, since, as [2, 30] assert, the OTT is more reliable than distance techniques as it doesn't use averaging techniques. It effectively represents the underlying hierarchical structure and the amount of organization in a given cognitive structure. It has the obvious disadvantage that difficulty during free recall might hide the underlying organization, which can be taken care of by using [30]'s technique which eliminates that possibility by providing subjects with a list of the relevant concepts. Once the ordered tree is formed for every subject, the regions based on this organisation are fed into the model, so that the model is individualized.

Actual distances were used as edge-weights between different nodes. Now, for this to work, the representation of each region as a single point needs to be individual specific: for example, depending upon whether we represent a region through an 'anchor-point' [31, 32] or the 'centroid'[18] (the spot in the region visited most often or having the highest significance) or the mid-point of the region, the weight will change. But as described in [31], while the concept of 'anchor points' is hard to define, at the same time there are also problems with representing the anchor points operationally and identifying them in individual cognitive representations. Mid-points are ineffective in the sense that humans hardly represent a region by its mid-point, since most of the time there is no structure at that point and alternative methods like the most familiar place score higher when ease in remembering is concerned. So, we represented each region with the centroid, which differed from one individual to another, and was found out for each subject through interview, based on which place they frequented the most in a particular region. While previous works mentioned beforehand pointed to directional and distance biases that distort the actual topological values, since these distortions are systemic ([33]), they would not affect the present model if we assume that the scaling is perpetuated to all the regions, so that the distance is scaled similarly for all the distant regions (i.e. the distances of all regions are over-estimated by the same factor) and the same happens for all the places within a region (all are under-estimated by the same scale), which is a fair assumption. In fact, while a lot of research is in favour of the power law in distance judgements ([34–36]), as [37] points out, 'the actual subjective unit used by each observer is not and can not be known'. [38] also contests the validity and usefulness of such a law and as such it is counter-intuitive to use that in a model. Furthermore, they are more accurate for long distances (*cognitive distance* [38]) and the maximum distance between any two places in our model is 1 mile between Hall 7 and the Air Strip. Anyway, even if a power law is used, all the distances will be similarly scaled, thereby leading to the same decisions as they would be in the actual case. So, using actual distances, even in the light of evidential support for distance-estimation distortion, would not be detrimental for the proposed model.

2.2 Operationalization of the Three Strategies

We briefly describe the three techniques presented in [1] and explain their implementation.

Fine-to-coarse method The heuristic depends on the *focal representation* of the regionalised environment. At the start of the navigation task, the region containing the start point is represented in full detail, whereas distant places are represented through a single representative - the region they are included in. For example, from the IITK campus map, suppose person A represents regions grouped as [(H1, H2,H3,H5,Tennis court),(MT, Air Strip, Environmental Building), (HC, KV), (LHC, WL, Lib, FACB), (Audi, ShopC, CC)] and he has to start from H1 and has to visit Tennis court, CC and Lib. In the focal representation at the beginning, he sees H1, H2, H3, H5, Tennis court, MT, HC, LHC and Audi (assuming they are the respective centroids), so that the start region is fully represented and distant regions are represented through the respective centroids. Now based on the estimated distance, the next stop would be Tennis court, which is inside the region and nearest to H1 and the next *focal representation* would remain the same. On next decision, A estimates that the region containing LHC is closer to the Tennis court than the Audi, thereby deciding on Lib as the next target and so on. The structure of our nodes and super-nodes facilitates this representation. When A starts from a node, the siblings are the only nodes it needs to check (using Dijkstra's algorithm) and decides on which region to visit next. Once that is done, A jumps to the super-node that contains the destination and in the process takes the optimal(shortest) path from start to first target (unlike in [18], A does not go to the centroid of the target region, but just uses the centroid to decide which region to go to and then takes the topologically shortest path from start to target place, and not the centroid of the target region). When A reaches the first target, that becomes the new starting point and being in the new super-node corresponding to target, it can employ the same tactic once again, till it exhausts all the targets.

Cluster Based Decision The technique, first proposed by [13], assumes that while deciding on our route, we are biased towards the region which contains the maximum number of targets, irrespective of its distance from the present location. So, in the implementation, the algorithm decides the region with the highest number of target locations, jumps to the nearest target in the region and exhausts all the targets in that region before going through the decision cycle again.

Least Decision Load The less number of decisions one has to take, the less likely he is to get lost. [1] show considerable evidence that this method is followed a lot while deciding on the navigation strategy. In a familiar environment, such as in a college campus, this decision load simply translates to the number of turns one takes while navigating and the number of decisions one has to take at each turn. In fact this crude method of complexity was used by [1], where they simply added up the possible movement decisions along the path. So, for this heuristics, the edge weights were the number of turns one has to take while going from A to B (even if no decision is to be made at a turn if it is the only existing turn to take, a straight line appears to present less cognitive load nonetheless, and hence, subjects delay the turning decision as long as possible, as ascertained by [17, 39]), and the number of possible decisions one has to make at each turn (thereby increasing the weight of cross-roads etc.). Now, the same approach that was followed in the *fine-to-coarse* method is used, with the new edge weights.

2.3 Randomized Decision Process

Humans are hardly deterministic in nature while planning something. [40] asserts that some subjects plan the whole route before setting out whereas some make just partial plans. Suppose A started with a navigational operation with the *cluster* technique in mind. So, he will first try to visit the region which has the maximum number of target objects. But once he is there, there is no guarantee that he will again follow the *cluster* technique. If we look upon decision making while navigating as a discrete process which goes on till all the targets are exhausted and not something that gets fixed or determined at the very outset, then there is a finite probability that the navigator will change their navigation strategy mid-way. In fact, existing literature supports this hypothesis. [3] has shown that human behaviour and wayfinding procedure changes with routes and surroundings. [41] suggests that problem in ascertaining a complete picture of the environment impedes the wayfinding task and this might lead to a change in the heuristic. [9] describes many reasons, like 'coasting', traffic, emotional state that influence the navigation strategy, supporting them with verbal reports. So we assume that any particular heuristic is not followed throughout the navigation task. When a subject has exhausted all the targets in a particular region and is at the last target for that region, we assume that when they plan ahead for the next target, they will start the process all over again, with the present location as the starting point and the remaining target points as the set of destinations. We assume it to be a *memoryless stationary stochastic process*, which can be thought of as restarting after each event is completed, the event being defined as the exhaustion of all the targets in the present area. The decision to choose a particular strategy out of the three at this point will be assumed to have no relation to their previously followed strategy (thus memoryless – which is a safe assumption for most of the daily life situations like shopping etc. In such scenarios, the time and attention given to the task at hand is enormous and when one is done with the objective and starts route planning again, it is theoretically not different from what they would have done had they started at the same point with the same set of target destinations that they now have). The stationary assumption asserts that the probability of choosing one method out of the three doesn't change from event to event during a task (as has been described, the path following heuristic might change based on many factors, but the probability of choosing one method over the other reflects the tendency of a subject to favor one method over the other and that tendency is usually inherent in the subject and not very heavily influenced by environmental factors; anyway, if some serious unforseen environmental anomaly forces the subject to choose a path heuristic that they otherwise avoid, such a thing can not be predicted in a general model in any case. Therefore, even though the process isn't strictly speaking a stationary one, it can be approximated with a stationary process, a practice which is prevalent in statistical methodologies). To make it clear, suppose the subject followed the *cluster* technique to enter region A' and now is at the last destination in A', say A. Once he is done with his work in A, suppose he has more destinations to go to in regions B' and C'. Now, based on his personal bias, he can employ any of the three heuristics at the moment, irrespective of what he followed beforehand (viz. the *cluster* strategy). While [1] proposed that all the three strategies are equally favoured, they did not have any concrete evidence to support the same. In fact, as was later observed, individuals are biased towards one strategy over the other to some extent. For example, while some subjects always tended to follow the *cluster* strategy, some others always went for the *fine-to-coarse* heuristics, and yet others used them interchangeably. To incorporate this phenomenon into the model, we assigned probabilities α, β and γ (corresponding to the probability of following *fine-to-coarse*, *cluster* or *least-decision-load* respectively), with $\alpha + \beta + \gamma = 1$, to the three heuristics and these were evaluated on a person to person basis so that they reflected that subject's tendency to follow a particular heuristics. Responses of the model based on variables α, and β were compared to actual response of the subject to arrive at the optimal parameters for the person. So, when the targets corresponding to a region are done away with, the model randomly selects one of the three heuristics with respective probabilities to follow next, and the navigation starts all over again with remaining target points. In case there is a tie, i.e. the chosen heuristic predicts two equally possible next destinations, the tie is resolved by choosing one of the two remaining heuristics according to their respective probabilities and so on.

2.4 Similarity Matching

To prove the validity of the model, we need to match the outcomes with actual responses of the subjects. For want of a better method, we resorted to string matching of the program output and the responses of the subject. String metrics have been abundantly used in DNA sequence matching and data mining, and as such, they seem a natural choice to gauge the similarity between modelled and experimental data. We used the Jaro-Wrinkler string metric for comparison. It is very efficient for matching of small strings (the number of destinations is less than 10, leading to strings of length less than 10), and [42] assert that it is one of the best string metrics available.

To create the ordered tree of spatial information, we used the TIGER program by [8, 23]. The rest of the algorithm was implemented in JAVA.

3 Experiment

The model was validated through an experiment.

Subjects Ten male IIT Kanpur undergraduates (seniors), in the age group of 20 to 24 years, participated in the experiment. All subjects had spent the last 3.5 years on the campus, in one of the halls of residence, and the primary mode of travel they followed was either walking or cycling.

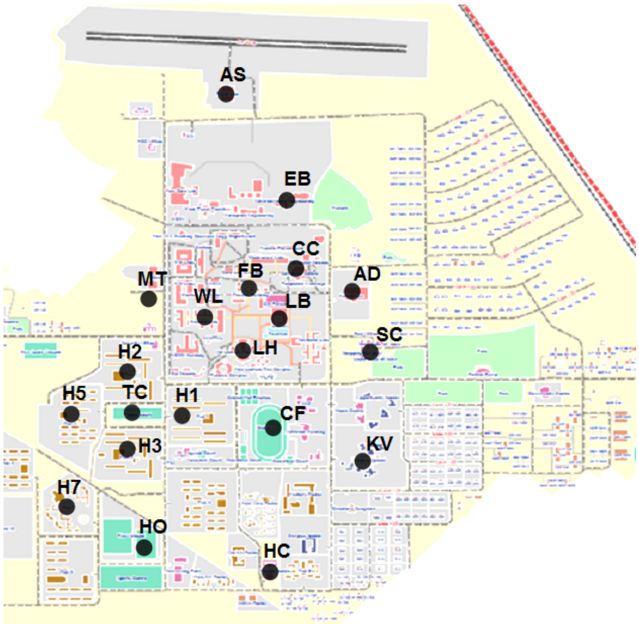


Fig. 1. IIT Kanpur Map with the dots showing the 20 places being investigated

3.1 Subjective Region Determination

The subjects were first asked to put down as many different places inside the campus as they could remember. Because of the length of the task, only 20 most recurring places of the responses were taken into consideration (refer to Figure 1, where these landmarks have been marked). These places were (the name in bracket indicates the name by which the place has been represented in the attached map): Hall of Residence 1 (H1), Hall of Residence 2 (H2), Hall of Residence 3 (H3) and Hall of Residence 5 (H5), Tennis court (TC), Hall 7 (H7), Hockey Field (HO), Cricket Field (CF), Health Centre (HC), Kendriya Vidyalay (KV), MT (MT), Airstrip (AS), Environmental Engineering Building (EB), Western Labs (WL), Lecture Hall Complex or LHC(LH), Faculty Bldg or FacB (FB), Computer Center (CC), Auditorium or Audi(AD), Shopping Center or ShopC (SC) and Library or Lib (LB).

The subjects were then given this list of 20 landmarks and instructed to memorize them with a goal to be able to recall each item without miss. Even though they were asked to memorize the places, following [30], to eliminate the possibility that difficulty during free recall might hide the underlying organization, they were provided with permutations of the 20 places on each recall and then they were asked to arrange them in vertical order in such a way that places they perceive are close together appeared close to each other in the list. The recall procedure was repeated 12 times, interspersed with distractor tasks , with 9 of them being cued and 3 non-cued (in cued trials, subjects needed to do the same, except that they had to begin with a particular word, called a cue, which were preselected), with the cued trials taking place at the first, sixth and tenth trials. The responses were given as input to the ordered tree algorithm and based on the output tree, the individualized regions for each subject were determined. Once the regions for a subject were identified, the subjects were asked to identify the place they visited the most in every region, so that that would become the centroid in the model.

3.2 Parameter Estimation

After a gap of five days, the subjects were presented with ten way finding tasks. In each of the tasks, the subjects had to start at a specified place (one of the 20, usually the hall of residence they resided in, to better approximate real way finding scenario of shopping etc.), visit a certain number of places, that varied from a minimum of five to a maximum of ten in number, do a hypothetical job that lasts from 5 to 10 minutes, and return back. Given this hypothetical situation, the subjects were asked to note down the sequence of places they would visit to accomplish the objective optimally in each of the situations.

From the above, ten strings from each subject were acquired. Eight of them were given as input to the way finding algorithm, to train the model and find the optimal α, β and γ for every subject separately. The algorithm varies α and β, with γ being automatically determined since $\alpha + \beta + \gamma = 1$. Based on the values of the parameters in each loop, it determines the expected route to be taken by each subject, outputting a string consisting of the same destinations as were given in the experiment. This expected route-string is compared with the one got from the subject during the experiment, and their similarity index, found using the Jaro Wrinkler distance metric, is plotted against α and β (refer to Figures 4 for graphs pertaining to this). Heuristically, for a particular subject and a particular test string, the parameters corresponding to the central point of the region defined by "the region where similarity index is greater than 0.7" are chosen as α, β and γ for that particular string. The same process is carried out for all the eight training strings for a particular subject, and their average is taken as the representative α, β and γ for that particular subject. Once these parameters for all the subjects have been found out, for each subject, employing these parameters, the expected route for the test case destinations is found out. These are compared with the two test strings (of the ten strings per subject found from the experiment, as explained before, eight were used to train the model and the rest two for testing it), and the similarity index is determined to validate the working of the model.

4 Results and Discussions

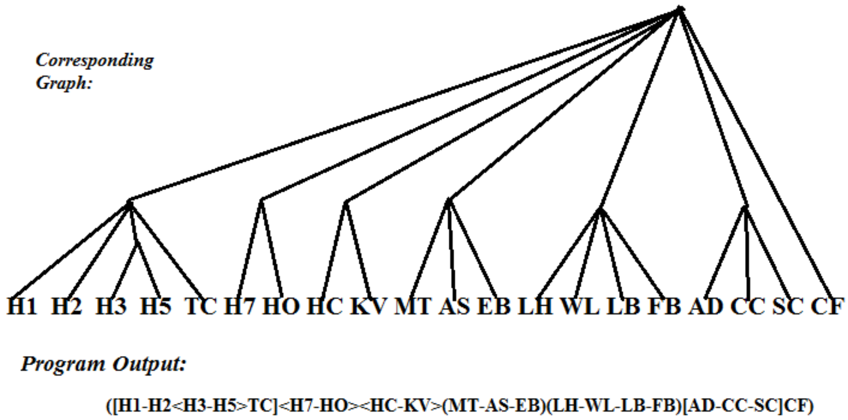
As described before, the aim of the experiment was to validate the computational model and to find out the trend in the tendency to support one navigation scheme over the other. While [1] conjectured that way finding is a linear combination of all the three methods with equal weights, our experiments revealed a general tendency to favour the *fine-to-coarse* method over all else.

In the recall tasks, as was expected, the region boundaries varied from subject to subject. For example, *Subject 1* had the following grouping of regions: (H1, H2, H3, H5, Tennis Court), (H7, Hockey Court, Cricket Field), (HC, KV), (MT, Airstrip, ENV) and (WL, LHC, FacB, CC, Audi, ShopC, Lib). On the other hand, *Subject 3* considered Cricket field as a separate region all by itself. He also considered (CC, Audi, ShopC) as a separate region while the rest were grouped as in *Subject 1*'s output. Figure 2(a) shows the output of the ordered tree algorithm for *Subject 3*, and Figure 2(b) is the corresponding hierarchical organization when the way finding task starts from H1– so that that region is completely laid out, with further regions being considered as a single node.

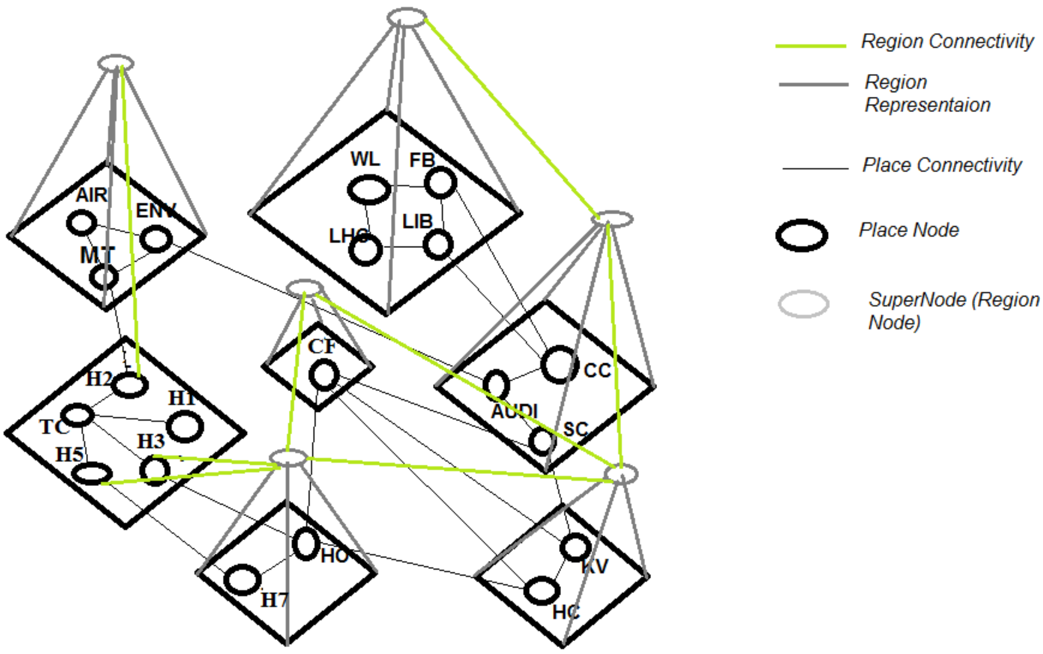
We may now make a few observations on the patterns emerging here (please refer to Fig. 1 for the locations). The subjects were undergraduates who mostly frequent the residential halls and the Academic Area, which is a walled sub-region in the map (the square region containing the nodes WL, LH, FB, LB and CC). Now note that of these nodes, four are in one of the regions, but CC is in another region with AD (Audi) and SC. This is despite the fact that there is a wall between Audi and the CC. This has arisen because the paths from to the FB/LB/LH etc. use a different gate on the walled area, near H1, whereas the CC is accessed through a gate in the wall closer to AD. Thus, the separate association between the CC and AD is quite natural and several subjects exhibited this clustering. Also, Airstrip and EB are separated by a separate wall, but they have a gate between them. Both are less frequented places. So are the Health Center (HC) and KV. Thus, we notice that, the least frequented places are grouped in larger regions, i.e. there is less detailed regionalization for less frequented places. Thus, MT and Airstrip are grouped in the same region even though they are very far away, and same is the case with KV and HC. Also, though the EB seems close to CC, the path between these is considerably longer than the euclidean distance, and also very few students visit the EB from the CC, so this is an extremely infrequent routing. Thus, though the EB and airstrip (AS) seem far apart, they may be subjectively viewed as belonging to the same, infrequently visited region.

We also note that *Subject 1* includes the cricket field in a region far away from it spatially. This was true of two other subjects. This may be because these subjects had a predisposition towards including the cricket field with the hockey field since these two spaces are conceptually associated. To eliminate any consequences of this anomaly on the parameter estimation in our experiment, the set of targets given to the subjects never included the cricket field.

The experiments helped in finding out the parameters for each of the subjects individually, on a subjective basis. For the ten subjects, the optimal average α lied between 0.4 and 0.9, while β and γ were in the interval (0.1, 0.6) and (0.0, 0.3) respectively, with the average value for the three over all the subjects being 0.55, 0.35 and 0.10 respectively. The average string similarity index for each



(a) The Ordered Tree



(b) Focal Representation for Wayfinding from H1

Fig. 2. Regionalization and Focal Representation for *Subject 3*: The first figure represents the ordred tree algorithm output for this subject, based on which the regions are defined as in the second figure. For a way finding task with H1 being the start point , this is the focal representation.

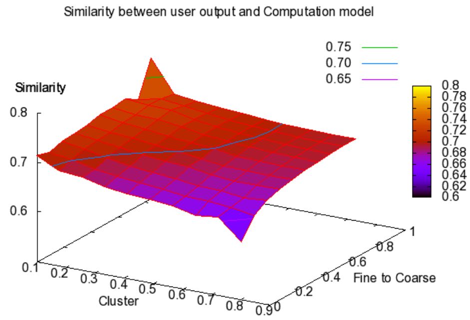
subject lied between 0.76 and 1.0 (for perfect match), with the average over all the ten being 0.84.

Subject-string	Model output	Similarity Index
[KV, HC, MT, WL, LHC, AUDI]	[HC, KV, MT, LHC, WL, AUDI]	0.89
[LHC, WL, FB, CC, H7, HO, MT]	[MT, LHC, WL, FB, CC, H7, HO]	0.90

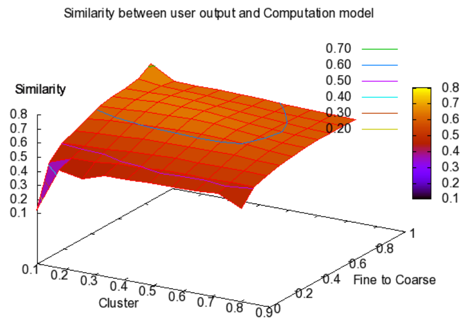
Table 1. Comparison of subject response and model output for *Subject 1*

For example, for *Subject 1*, after training over the eight train-strings, the optimal α, β and γ were found out to be 0.5, 0.45 and 0.05 respectively. Figure 3(a) shows the similarity index for the first input of the training set([TC, EB, WL, LB, CC, AD, KV] traversed in that order by the subject). As can be seen, the central point of the region where similarity index is greater than 0.7 is approximately $(\alpha, \beta, \gamma) \equiv (0.7, 0.2, 0.1)$. Similarly, the 3-tuples for each one of the eight strings was determined, and their average is what has been mentioned as the optimal parameters for this subject. These were set as the parameters for the model for the test run. The test sequences were [KV, HC, MT, WL, LHC, AUDI] and [LHC, WL, FB, CC, H7, HO, MT], and the outputs given by the program were [HC, KV, MT, LHC, WL, AUDI] and [MT, LHC, WL, FB, CC, H7, HO], giving rise to similarity indices of 0.89 and 0.90 respectively (refer to Table 1). From Figure 3(b) also we notice that when the model predicts primarily *least-decision-load* based way finding ($\gamma \approx 1$) while the subject has followed primarily the *fine-to-coarse* method for that particular string (the experimental string is [LHC, MT, AS, H7, HO, HC, KV] for *Subject 3*, which can easily be verified to adhere to *fine-to-coarse* methodology), the similarity index is close to 0.2. Similar trends have been seen in other train-strings also, and this justifies the use of the string metric as an acceptable measure of the models efficiency. When the model is known to predict the wrong outcome (based on the wrong parameters), the similarity index of the outcome and the train-string are very low. And correct prediction has a high similarity index greater than 0.65. So the heuristic of taking any similarity greater than 0.7 as a good approximation is justified. Similarly also, a high similarity index between the output of the model and a test string truthfully reflects the validity and prediction capability of the model. As such, an average similarity index of 0.84 over all the test cases from the ten subjects is testimonial to the fact that our model is very good at predicting individual way-finding behaviour.

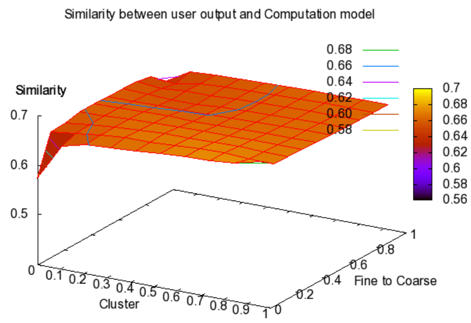
[1] conjectured that the weights for all the three way finding techniques are equal, i.e. we are equally likely to follow any one of the three techniques. If that were the case, ideally, the optimal value of α, β and γ would have been 0.33 or some number very close to the value. But as was seen in the above discussion, the optimal values came out to be $(\alpha, \beta, \gamma) \equiv (0.55, 0.35, 0.1)$, showing a prevalent



(a) Similarity matching for train data (TC, EB, WL, LB, CC, AD, KV) for *Subject 1*



(b) Similarity matrix base case justification



(c) Primarily cluster based wayfinding tendency of *Subject 5*

Fig. 3. Graph for Similarity index vs. α and β for a few cases. The parameters for fine-to-coarse and cluster strategies have been varied, with that for the least decision load being $1 - \alpha - \beta$. The similarity indices between model output and user/subject string has been plotted for all possible variation of these three parameters.

tendency among the folks to follow the *fine-to-coarse* method of way finding, at least inside the regionalized IIT Kanpur campus.

Here, it is also worth noting that, the tendency to follow any one method is highly subjective. As mentioned, while most of the subjects were primarily biased towards a *fine-to-coarse* strategy of way finding, the decision on following any one method varied from person to person and also from trial to trial. For example, *Subject 5* showed a predisposition towards the cluster strategy alone, visiting those regions which had the highest number of targets in succession irrespective of the distance, in 7 out of the ten tasks. Figure 3(c) shows the graph for one of such trials and we can easily see that the highest similarity index occurs for $(\alpha, \beta, \gamma) = (0, 1, 0)$. The fluctuation in the tendency to follow a method is also apparent in the responses of the subjects. For example, *Subject 2*, while given the destinations of [WL, AS, SC, AUDI] and [SC, CF, EB, MT, AS], chose to traverse the first list in [WL, AS, AUDI, SC] and the second in [AS, MT, EB, CF, SC]. As can be easily ascertained, the first response is in adherence to *fine-to-coarse* method, while the second follows a cluster method. Similarly, even though *Subject 1* essentially followed a *fine-to-coarse* method of way finding, whenever Airstrip was included in the target set and the start point was Hall 1, the subject invariably went there first, showing a tendency to follow *least-decision-load* or ISS strategy ([17]).

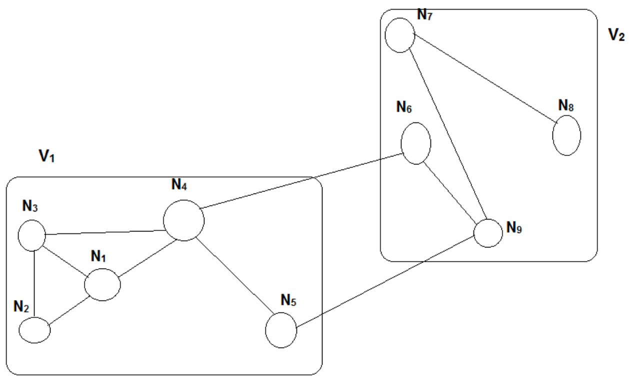


Fig. 4. Graphical Regionalized Representation

We might begin to interpret this trend in the following way. Refer to Figure 4. Lets suppose all the places in a regionalized environment are represented by nodes. They have been numbered N_1, N_2 etc. The regions that encompass these places are represented through V_1, V_2 etc. Now, while a subject is involved in way finding task in a familiar environment, we assume that he is abreast with all the information related to any particular node, thanks to his familiarity with the area. This is stored in his long-term memory. But at the time of way finding, considering that working memory has a limited capacity, it is much more computationally efficient to just have a representation of the region he is in in detail, and to represent other regions as a single node. For example, if the subject is in N_1, it is necessary for him to have a representation of N_2 through N_5 in full detail, as he has to navigate the immediate vicinity; but at the same time he can do with representing N_6 through N_7 with a single V_2, which is the basis of hierarchical organisation. In this way, being a cognitive miser, he can defer the exact plan-out for targets in V_2 till the time he actually gets in there. Mathematically put, suppose there are i regions in the familiar area, numbered V_1 through V_i, and let the maximum number of places in any region be k. Now, if the working memory needs to hold the full information of the entire area, it would be proportional to $k \times i$. On the other hand, if he represents only the present region in detail and distant regions as a single node, the information content is proportional to $k + i - 1$. This favours the hierarchical organisation. Now given a set of target points, if the subject follows the *fine-to-coarse* method, in addition to the hierarchical representation, the only other information that he needs to store in his working memory is that of which target regions to visit. Once he visits the regions by taking the shortest path, he can later worry about which exact target places to visit in that region, the detailed map of which he can access once he gets there. On the other hand, if he is inclined to use the *cluster* method, in addition to storing the target region information, he would also have to store how many target places are there in each region to optimally visit and execute the way finding task (it "takes into account the distribution of target locations within an environment"[1]), which puts a bit of extra effort on the working memory. This, added with the tendency to minimize path length, might what prompt a subject to be more inclined towards the *fine-to-coarse* method. According to the same logic, the *least-decision-load* should have been followed the most, as it demands the least burden on the working memory. However, the subjects, even though they are cognitive misers and would prefer to take minimal decisions, also have the goal of optimally completing the task in the least possible time, and given the fact that a path of least decision does not usually (or logically - logically since *fine-to-coarse* and *cluster* methods can guarantee the best possible optimal path, while *least-decision-load* method just defers the decision to a later time, thereby leading to the possibility of going through a suboptimal path as far as time and effort are concerned) achieve that goal, this might be the reason for its being followed the least.

On another note, the *least-decision-load* strategy usually comes into play when we have alternative paths for the same target location and one path is much more complex than the other. " Such a strategy could be employed, because the risk of getting lost is smaller on less complex routes" [1]. However, as is evident from the campus map, the path between the places selected are hardly complex and most of the time the alternative path is as complex as the initial path. This reduces the tendency to fall back on the *least-decision-load* strategy. In fact, this can be an indication that this heuristic is less likely to be followed in highly structured and uncomplicated environments (e.g. rural areas) and might only come into play in large urban areas where two places can be connected in myriads of different and complicated ways, thereby necessitating a minimization of the number of decisions to be taken.

5 Conclusion and Future Work

In this work, we investigated three path finding heuristics for wayfinding in hierarchical maps as proposed by [1]. We looked into their relative efficacy in predicting human behaviour by comparing their results against paths obtained from subjects for a campus map. Assuming a hierarchical model of spatial memory, we first obtained each individual's subjective regionalization on the familiar space, using [2]'s ordered tree algorithm. Our results indicated that while [1] suggested that all the three methods are equally likely to be followed, the subjects had a greater inclination towards the *fine-to-coarse* heuristics. Even though the exact method followed varied from subject to subject and task to task, nonetheless, an overall tendency to favour the *fine-to-coarse* over the other two was clearly evident. We also tried to provide an explanation based on working memory hypothesis and the properties of the regionalized environment like the college campus to explain this trend, though this needs to be validated.

A number of factors skew the responses of humans in way-finding tasks. These include vagueness of region boundaries, distance and direction distortion across regions, subjective bias in way-finding heuristics, random change in the particular heuristic being followed wihin a task from one location to another, etc – which we have attempted to include in the present model, albeit in a primitive way. Thus, this model, though it captures some of the salient aspects, much work remains in terms of understanding cognitive process of wayfinding.

Constructing computational models for such domains is a serious challenge since the operational hierarchical representation of the space varies from individual to individual. Following the work of [8] we have outlined a process for identifying a plausible regionalized map, and then have implemented the three strategies as proposed in [1]. This enables a computational simulation to judge possible wayfinding responses of humans based on various data.

At this point, we have only considered familiar environments. However, it is possible to encode initial regions in terms of a clustering algorithm, and use these regions to evaluate way-finding strategies as above. Such methods hold great potential for guiding the design of information for new spaces, or other tasks of relevance to spatial navigation. Thus, in addition to the cognitive aspects - that one particular wayfinding strategy may be recruited more often than others - a computational tool by itself is a valuable resource for a number of applications.

References

1. Wiener M. J., Schnee A., and Mallot H.A. Use and interaction of navigation strategies in regionalized environments. *Journal of Environmental Psychology*, 24:475–493, 2004.

2. J. Reitmann and H. Rueter. Organization revealed by recall orders and confirmed by pauses. *Cognitive Psychology*, 12:554–581, 1980.
3. R. Golledge. Path selection and route preference in human navigation: A progress report. In Andrew Frank and Werner Kuhn, editors, *Spatial information theory: a theoretical basis for GIS (COSIT95), No. 988, Lecture Notes in Computer Science*, volume 988 of *Lecture Notes in Computer Science*, pages 207–222. Springer Berlin / Heidelberg, 1995.
4. M. Dry, M. Lee, D. Vickers, and P. Hughes. Human performance on visually presented traveling salesperson problems with varying numbers of nodes. *Journal of Problem Solving*, 1(1):20–32, 2006.
5. B. Golden, L. Bodin, T. Doyle, and W. Stewart. Approximate traveling salesman algorithms. *Operations Research*, 28:694–711, 1980.
6. J. M. Wiener, N. N. Ehbauer, and H. A. Mallot. Planning paths to multiple targets: memory involvement and planning heuristics in spatial problem solving. *Psychological Research*, 73:644–658, 2009.
7. R. Passini. Spatial representations, a wayfinding perspective. *Journal of environmental psychology*, 4(2):153–164, 1984.
8. S. Hirtle and J. Jonides. Evidence of hierarchies in cognitive maps. *Memory & Cognition*, 13:208–217, 1985.
9. Hugo J. Spiers and Eleanor A. Maguire. The dynamic nature of cognition during wayfinding. *Journal of Environmental Psychology*, 28:232–249, 2008.
10. R.C. Dalton. The secret is to follow your nose: Route path selection and angularity. *Environment and Behavior*, 35(1):107131, 2003.
11. H.J. Spiers and E.A. Maguire. Spontaneous mentalizing during an interactive real world task: An fMRI study. *Neuropsychologia*, 44(10):1674–1682, 2006.
12. J. Wiener and H. Mallot. Fine-to-coarse route planning and navigation in regionalized environments. *Spatial Cognition and Computation*, 3(4):331–358, 2003.
13. C. Gallistel and A. Cramer. Computations on metric maps in mammals: getting oriented and choosing a multi-destination. *Journal of Experimental Biology*, 199(1):211–217, 1996.
14. M. ONeill. Effects of familiarity and plan complexity on wayfinding in simulated buildings. *Journal of Environmental Psychology*, 12:319–327, 1992.
15. R. G. Golledge, T. R. Smith, J. W. Pellegrino, S. Doherty, and S. P. Marshall. A conceptual model and empirical analysis of children's acquisition of spatial knowledge. *Journal of Environmental Psychology*, 5:125–152, 1985.
16. T. Gärling and E. Gärling. Distance minimization in downtown pedestrian shopping. *Environment and Planning A*, 20:547–554, 1988.
17. J. N. Bailenson, M. Shum, and D Uttal. The initial segment strategy: A heuristic for route selection. *Memory & Cognition*, 28:306–318, 2000.
18. D. Leiser and A. Zilbershatz. The traveller: A computational model of spatial network learning. *Environment and Behavior*, 21:435–463, 1989.
19. E. Chown, S. Kaplan, and D. Kortenkamp. Prototypes, location and associative networks (plan): Towards a unified theory of cognitive mapping. *Journal of Cognitive Science*, 19:11–51, 1995.
20. R. Chavarriaga, T. Strosslin, D. Sheynikhovich, and W. Gerstner. A computational model of parallel navigation systems in rodents. *Neuroinformatics*, 3:223–241, 2005.
21. Girard B, Filliat D, Meyer JA, Berthoz A, and Guillot A. Integration of navigation and action selection functionalities in a computational model of cortico-basal-gangliathalamo-cortical loops. *Adaptive Behaviour*, 13:115–130, 2005.

22. L. Dolle, M. Khamassi, B. Girard, A. Guillot, and R. Chavarriaga. Analyzing interactions between navigation strategies using a computational model of action selection. In *Proceedings of the international conference on Spatial Cognition VI: Learning, Reasoning, and Talking about Space*, pages 71–86, Berlin, Heidelberg, 2008. Springer-Verlag.
23. Stephen C. Hirtle. *TIGER: Buiding Ordered Trees.* `ftp://ftp.pitt.edu/group/csna/Hirtle/Dos/Tiger/`.
24. Barbara Tversky. Functional significance of visuospatial representations. *The cambridge handbook of visuospatial thinking*, pages 1–34, 2005.
25. A. Stevens and P. Coupe. Distortions in judged spatial relations. *Cognitive Psychology*, 10:526–550, 1978.
26. B. Kuipers. The spatial semantic hierarchy. *Artificial Intelligence*, 19:191–233, 2000.
27. B. Scholkopf and H. A. Mallot. View-based cognitive mapping and path planning. *Adaptive Behavior*, 3(3):311–348, 1995.
28. G. Franz, H. Mallot, and J. Wiener. *Graph-based models of space in architecture and cognitive science - a comparative analysis. Architecture, Engineering and Construction of Build Environments.* Windsor, Ontario, Canada, 2005.
29. D. Montello, M. Goodchild, J. Gottsegen, and P. Fohl. Where's downtown?: Behavioral methods for determining referents of vague spatial queries. *Spatial Cognition and Computation*, 3:185–204, 2003.
30. M. Naveh-Benjamin, W.J. McKeachie, Y.G. Lin, and D.G. Tucker. Inferring students' cognitive structures and their development using the 'ordered tree technique'. *Journal of Educational Psychology*, 78:130–140, 1986.
31. H. Couclelis, R. Golledge, N. Gale, and W. Tobler. Exploring the anchor point hypothesis of spatial cognition. *Journal of Environmental Psychology*, 7:92–122, 1987.
32. R. G. Golledge, , and A. N. Spector. Comprehending the urban environment: theory and practice. *Geographical Analysis*, 10:403–426, 1978.
33. T. P. McNamara and V. A Diwadkar. Symmetry and asymmetry of human spatial memory. *Cognitive Psychology*, 34(2):160 – 190, 1997.
34. R. Briggs. Urban cognitive distance. In R. M. Downs and D. Stea, editors, *Image and Environment.*, Chicago: Aldine, 1973.
35. M. Cadwallader. Problems in cognitive distance and their implications for cognitive mapping. *Environment and Behavior*, 11:559–576, 1979.
36. E. K. Sadalla and L. J. Staplin. The perception of traversed distance. *Environment and Behavior*, 12:183–193, 1980.
37. T. Engen. Psychophysics: Ii - scaling methods. In J. W. Kling & L. A. Riggs, editor, *Woodworth & Schlosberg's Experimental Psychology*, pages 47–86. Holt, Rinehart and Winston, 1971.
38. Montello D.R. The measurement of cognitive distance: methods and construct validity. *Journal of Environmental Psychology*, 11:101–122, 1991.
39. N. Christenfeld. Choices from identical options. *Psychological Science*, 6:50–55, 1995.
40. C. Holscher, T. Meilinger, G. Vrachliotis, M. Brosamle, and M. Knauff. Up the down staircase: Wayfinding strategies in multi-level buildings. *Journal of Environmental Psychology*, 26(4):284 – 299, 2007.
41. S. Werner and P. Long. Cognition meets le corbusier cognitive principles of architectural design. *Lecture Notes in Artificial Intelligence*, 2685:112 – 126, 2003.
42. William W. Cohen, Pradeep Ravikumar, and Stephen E. Fienberg. A comparison of string distance metrics for name-matching tasks. In *IIWeb*, pages 73–78, 2003.