Towards a Cognitive Model for Human Wayfinding Behavior in Regionalized Environments

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Abstract

Human wayfinding operates very very differently from traditional deterministic algorithms owing to a) restrictions in working memory resulting in subjective regionalized maps, and b) flexible adoption of different navigation strategies. While a number of cognitive strategies have been proposed for human wayfinding, these have been hard to evaluate thoroughly owing to a lack of computational simulation. In this work, we propose a stochastic approach for capturing these aspects, and argue for a memoryless, stationary implementation. In two longitudinal experiments on the same group of subjects, we first estimate the subjective regionalized maps for each subject on the same familiar spatial domain. Later, based on their wayfinding responses, we can estimate the stationary probabilities for different strategies. We apply this algorithm to evaluate three wayfinding strategies proposed in the literature, and repudiate the previously held suggestion that they are followed equiprobably.

Introduction

Humans frequently navigate paths in large-scale *familiar spaces*, and the cognitive mechanisms underlying such wayfinding have been studied over several decades (Golledge 1995; Dry et al. 2006; M. J., A., and H.A. 2004). Experimental techniques used include sketching (Passini 1984), ordering of sites based on recall (Hirtle and Jonides 1985), navigation paths on virtual scenes (M. J., A., and H.A. 2004), linguistic interactions (Spiers and Maguire 2008; Dalton 2003), as well as brain FMRI (Spiers and Maguire 2006). From the results of these studies, one observes two aspects in which cognitive approaches differ from traditional deterministic computational algorithms. First, space is not represented monolithic whole but hierarchically organized into regions. This regionalized map is acquired from experience and the representation of the same region can vary substantially between individuals. This structure helps decision-making within the same region, and is also conducive to restrictions in working memory. Secondly, there appear to be several heuristic strategies that explain various aspects of human navigation ability, such as the *fine-to-coarse strategy* (Wiener and Mallot 2003), the *cluster* method (Gallistel and Cramer 1996), the *least decision load* (ONeill 1992), the *least-angle strategy* (Dalton 2003) etc. Unlike deterministic algorithms, multiple strategies may be deployed by the same individual in different situations or at different times. This brings in a stochastic nature to the wayfinding process.

While these analyses are based on the psychological evidence, thorough testing of cognitive theories increasingly depends on simulation. Here the computational computational models that are available adopt approaches such as path-cost minimization (Gärling and Gärling 1988; Bailenson, Shum, and Uttal 2000), the *Traveler* (Leiser and Zilbershatz 1989) 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.

Another group of computational models approaches the problem by constructing plans that are tested via mobile robot navigation (Stober, Fishgold, and Kuipers 2009) Some approaches (Chee K. Wong 2007) also attempt to capture the notion of fragmentary (incomplete) plans, but it is essentially the first part of a Dijkstra-like optimal path based on a global map. While these models miss many relevant aspects to human computation, the dialogue between cognition and computation has nonetheless been effective. For example, the suggestion in (Chown, Kaplan, and Kortenkamp 1995) that paths are initially planned at higher abstraction levels, though it leads to contradictions in cognition (M. J., A., and H.A. 2004), is also the basis for the *coarse-to-fine* heuristic, a strategy that emerges as one of the more probable ones in our analysis below. On the whole, the computational model proposed so far are not realistic for cognitive way-finding, primarily because a) they fail to incorporate the regionalized maps and the subjectivity associated with it, and b) each model tends to incorporate only a single heuristic.

In this work, we combine a model for an acquired (subjective) hierarchical map of familiar spaces, along with a local search mechanism, which is stochastic, to model human way-finding behavior. That such a tool can be used to evaluate navigational strategies is demonstrated by considering three strategies described in (M. J., A., and H.A. 2004), where it was suggested that perhaps these three strategies are followed equiprobably. Using the approach outlined next, we show that within the three suggested approaches, the coarse-to-fine strategy is more likely to be selected than the others.

The Proposed Model

The model we propose emulates human way-finding behavior in very familiar environments. Examples of such environments include the place one lives in, or the place of work, or college campus for students–essentially a place where a person wouldn't need navigational help. An example of such a navigational task would be to decide which stores to go to first and which path to follow when you are going shopping with a predefined set of destinations. Our model doesn't incorporate human navigational behavior in unknown terrains. In the description that follows, we establish the claims the model is based on, and elaborate on them:

CLAIM 1: ***Human wayfinding operates very differently from traditional computational graph-based approaches.***

While wayfinding has been related to well-studied algorithmic problems such as human capabilities in solving the traveling salesman problem (Dry et al. 2006; Golden et al. 1980), it differs in three important aspects. First, the entire space is not available visually, so that working memory constraints come into play. Secondly, the large spaces involved call for granularity at different scales, and both representations and operations on these are considerably different (Wiener, Ehbauer, and Mallot 2009). And finally, it has the flexibility of adopting different navigation strategies, opportunistic modification, partial plans etc.

CLAIM 2: ***Familiar environments are hierarchically stored in the spatial memory, i.e. they are regionalized and the regionalization is subjective.***

A way-finding task in a familiar terrain implies we are not using any navigational help like maps etc. So, while deciding on the path to take for a certain number of targets, we are essentially representing the whole environment in our working memory so that we can find an optimal path going through all the target points. Considering that working memory has a limited capacity, it is much more computationally efficient to just have a detailed representation of all the landmarks in the region one is in (for navigation in the immediate vicinity), while farther landmarks can be grouped into their representative regions. The subject, a cognitive miser, thereby defers the exact plan-out for targets in those regions till the time they actually get in there.

In fact, what we are proposing here is not a radical idea, but a well-established one. 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 ((Tversky 2005; Hirtle and Jonides 1985)). The hierarchical model of spatial memory suggests that space is organized into a graph-like representation based on personal biases and spatial characteristics. Such a model has been argued for based on errors in distance and direction judgement (Stevens and Coupe 1978; Hirtle and Jonides 1985), as well as limitations of working memory (Tversky 2005).

We further argue that the hierarchical 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. Works by (Hirtle and Jonides 1985; Montello et al. 2003) assert as much. Our assumption about subjective hierarchical structuring of space can thus be considered reasonably valid.

Algorithm 1 Subjective Model Estimation

Input :

1. Set of strings containing recalled landmarks: $S = \bigcup_i \{T_i\}, T_i \,\epsilon\, \{\text{permute}(a_1, \ldots, a_n)\}$.
2. Set of training task objectives: $A = \bigcup_i \{A_i\}$; $A_i = \{\text{Targets}_i : \{a_{i1}, \ldots, a_{ik}\}, \text{Source}_i : \{b_i\}, \text{Response}_i : \{b_1, a'_{i1}, \ldots, a'_{ik}\}\}$
3. A repository of heuristic-functions: $\text{H} = \{H_1, H_2, \ldots, H_m\}$

Pseudocode :

1. $Tree$ = orderedTreeTechniqueOTT(S);
2. $G < V, E >$ = hierarchicalRegionalizedGraph($Tree$);
3. Training:

for A_i in A
  for $\forall\{\pi_1, \pi_2, \ldots, \pi_m\} \ni \sum_j \pi_j = 1$
    $source' = b_i$;
    $target'$ =copy($target_i$); $resp' = source$;
    while $target' \neq \Phi$ **begin**
      start at $source$;
      $r = \text{rand}(0, 1)$;
      if $r \epsilon (\sum_{j<s-1} \pi_j, \sum_{j<s} \pi_j)$ $nextTarget$ = followHeuristic ($H_s, source, G < V, E >$);
      $source = nextTarget$;
      $resp'$ =append($resp', source$);
      $target' = target' - nextTarget$;
      navigate to $source$;
    endWhile
    similarity $(\{\pi_j\})$ = JaroWrinkler($resp_i, resp'$);
  endFor
  $(\{\pi_j\})_i$ = centroid($\{Distribution(\{\pi_j\})|$ similarity $>$ 0.7 $\}$); **endFor**
Output: $(\{\pi_j\})$ = average$\{(\{\pi_j\})_i\ \}$

CLAIM 3: ***No single way-finding heuristic is adequate in accounting for human behavior. In fact, the human subject has, at its disposal, a*** **repository of navigational heuristics** ***to choose from, and the preponderance of those heuristics vary on a subject-to-subject basis.***

The Introduction of this write-up asserts that humans follow myriads of different heuristics for way-finding tasks. Navigation methods based on computational graph manipulation alone are inadequate to faithfully reproduce human behavior (Claim 1). One might argue that different but *specific* heuristics are followed in different environments, or by different subjects under different conditions. But (M. J., A., and H.A. 2004) have shown that they needed as many as three heuristics to properly explain way-finding behavior under exactly the same conditions.

It can thus be argued that any computational model emulating human behavior needs to have a *repository* of empirically proven heuristics, instead of relying on any single method. For our model, we limit ourselves to the three strategies of *fine-to-coarse, cluster, and least-decision load*, described in (M. J., A., and H.A. 2004). These three strategies have also been used as the basis for a number of other evaluations (Spiers and Maguire 2008; Wiener, Ehbauer, and Mallot 2009), and appear to have gained considerable acceptability as cognitive approaches for planning routes in a regionalized environment. Using particularly these three enables us to investigate their relative preponderance through experimentation, and at the same time validate/repudiate the authors'(M. J., A., and H.A. 2004) claim that they are followed equally likely. We defer the detailed description of these strategies till next section, where we describe how they have been implemented in the operationalization of the model.

CLAIM 4: ***A human subject switches between a set of heuristics during a way-finding task, and this behavior can be modelled through a*** **memoryless stochastic process.**

Humans are hardly deterministic in nature while planning something. (Holscher et al. 2007) asserts that some subjects plan the whole route before setting out whereas some make just partial plans. Considering navigation 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, it is likely that the navigator will change their navigation strategy mid-way. In fact, existing literature supports this hypothesis (Golledge 1995; Werner and Long 2003; Spiers and Maguire 2008).

We, therefore, assume that any particular heuristic is not followed *throughout* a single navigation task. Let's define an "episode" to be a plan fragment, which typically includes a sequence of targets in a region; more generally, it may be any subsequence of a plan. In our present work, exhausting all targets in a region constitutes an episode. We assume that an episode is conducted according to a particular heuristic. When a subject has exhausted all the targets in a particular region (the episode is over) and is at the last target for that region, they will start the process of path planning all over again, with the present location as the starting point and the remaining target points as the set of destinations.

The above description parallels that of a *memoryless stochastic process*, which restarts after each event (episode) is completed. The decision to choose a particular heuristic out of the repository at this point will be assumed to have no relation to their previously followed strategy (thus memoryless). [1] In other words, we assume that strategy for episode n is independent of episode $n-1$. That is, if

$$A = \{a_1, a_2, \cdots, a_k\} \quad (\textit{repository of k-heuristics})$$

and

$$X_n = \textit{Heuristic chosen in episode n}$$

then

$$Pr(X_n = a_i | X_m = a_j) = Pr(X_n = a_i)$$

$$\forall\, i, j \;\; and \;\; \forall m < n.$$

We further claim that the probability of choosing a method out of the repository doesn't change from episode to episode during a task. The path following heuristic might change based on many factors; but the probability of choosing one method over the other reflects a subject's propensity. And that is usually inherent in the subject and not very heavily influenced by environmental factors. Formally, the probability of choosing a particular strategy a_i at any episode n is independent of n.

$$Pr(X_n = a_i) = Pr(X_m = a_i) \forall\, n, m.$$

This thus leads to a *stationary* model. [2] While we are looking at the whole path finding process as a stochastic process, one might just concentrate on the episodes, and then the episodes can be looked upon as i.i.d. random variables.

We must make it clear though that dynamic effects (e.g. situations where the original objectives may be altered as the plan is being executed viz. opportunistic planning, or some serious unforeseen environmental anomaly that forces the subject to choose a path heuristic that they otherwise avoid) can't be accounted for in this model. Anyway, such anomalies can not be predicted in a general model. 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.

For the model at hand, $k = 3$, with $\{a_1, a_2, a_3\} \equiv$ {fine-to-coarse, cluster, least-decision-load}, and $Pr(X_n = a_i) = \alpha, \beta,$ and γ respectively for $i = 1, 2$ and 3. We also have $\alpha + \beta + \gamma = 1$.

CLAIM 5: ***The present computational approach permits simulation of complex situations that was not possible until now.***

While a number of strategies have been proposed for wayfinding (Introduction), these have not had the scope of being tested computationally. One of the challenges is that spatial representation models are regionalized, vary across subjects and are difficult to deal with. Given a memory representation, and a scope for incorporating different heuristics in a repository, the relative preponderance of the methods can be statistically evaluated. In fact in the two experiments we will describe presently, we considered the responses of a group of subjects for wayfinding in a familiar domain, and by fitting their responses to the model, we were able to compare the aforementioned three wayfinding strategies.

[1] This 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 one 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.

[2] One might argue that while we have divided episode based on regions, they might indeed have quite flexible boundaries. The best way we can think of to model that would be to treat the wayfinding as a Markov process, where the probability of choosing the next heuristic would be dependent on the previous one, there by accounting for dynamic episode boundaries. But as described in the previous footnote, the complexity of the task might leave such a complex model inefficient.

Implementation

We try out the model with the IITK campus as the natural familiar region, in which the way-finding tasks are to be perfomed. A map of the campus with the concerned target place-set is shown in Figure 1. In subsequent subsections, we chalk out the implementation of whatever was described in the previous section.

Hierarchical Graph Using OTT

We try to build subjective working memory representations of the campus, following Claims 1 and 2. The regionalized representation of the campus for each test subject was created by the ordered tree technique (OTT) proposed by (Reitmann and Rueter 1980), and used for similar purposes by (Hirtle and Jonides 1985)[3]. Once the ordered tree is formed for every subject, the regions based on this organization are fed into the following model, so that the model is individualized.

The landmarks/targets are implemented as topologically connected nodes of a graph, with their parent nodes(supernodes) representing the regions. When a token (person) is in a node, it can access all its siblings and representations of the other supernodes, to emulate the fact that when it's in a region, it can view that region in detail, but has to see other regions as a single entity (viz. the spot in the region visited most often or having the highest significance–*centroid*). [4] This is subjective, and was found out for each subject through interview. The edge weights are determined according to the heuristic followed.

The Three Strategies

Following arguments in Claim 3, we included three techniques presented in (M. J., A., and H.A. 2004) in our repository and we explain their implementation in detail. **Fine-to-coarse method** The heuristic asserts that the present region is represented *finely*, with every detail, and the rest are represented by points(*coarse*), and a shortest path is found to all the targets. For example, for [region{landmarks}] representation $[A\{a_1, a_2, a_3\}, B\{b_1, b_2, b_3\}, C\{c_1, c_2, c_3\}]$, targets $\{a_2, b_2, b_3, c_3\}$, source a_1, the algorithm tries to find a minimum spanning tree (Dijkstra's) from a_1 to $[a_2, B, C]$(regions, not landmarks) through the hierarchical graph. Once the token is in the first node of the nearest region/supernode(say C), having eliminated targets of the present region(A), the process restarts with new targets and the new source.[5] The edge weights are actual distance between landmarks (or in case of supernodes, distance between a landmark and a centroid).

[3]We use the modified technique of (Naveh-Benjamin et al. 1986)

[4]Other forms of region representation are mid-points (obviously flawed), or *anchors*(Couclelis et al. 1987; Golledge, , and Spector 1978), which are hard to define(Couclelis et al. 1987), and non-operationalizable.

[5]Unlike in (Leiser and Zilbershatz 1989), the token 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.

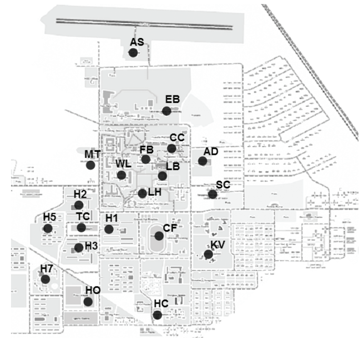


Figure 1: IIT Kanpur Map with the dots showing the 20 places being investigated

Cluster Based Decision The technique(Gallistel and Cramer 1996), assumes we first visit the region with the maximum number of targets, irrespective of its distance from the present location. So, the token, having exhausted the targets in the present region, jumps to the supernode with maximum targets(B in previous example), 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 (irrespective of distance). In a familiar environment, such as in a college campus, the 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 (M. J., A., and H.A. 2004), where they simply added up the possible movement decisions along the path. This algorithm is therefore easily implemented by just changing the edge weights to the number of turns one has to take while going from, say a_1 to B.

Stochastic Modeling When targets in the present region are exhausted, the strategy to be followed next is randomly choosen from the heuristics repository according to probabilities α, β, γ, as explained before. These parameters for each individual are found through Experiment 2.

To create the ordered tree of spatial information, we used the TIGER program by (Hirtle and Jonides 1985; Hirtle). The rest of the program was implemented in JAVA.

Experiments

Two experiments were conducted, to figure out the subjective hierarchical representation of spatial memory for each individual, and their propencity for any particular heuristic (Claim 5).

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.

Expt 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).

The landmarks were then regionalized, the regions being tailored for each subject, by providing the recall procedure output described in (Naveh-Benjamin et al. 1986) [6] as the input to the OTT.

Expt 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 [7], 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 subjective α, β and γ (i.e. $\{\pi_1, \pi_2, \pi_3\}$ in Algo 1). 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 [8] , is plotted against α and β (refer to Figures for graphs pertaining to this). Heuristically, for a particular subject and a particular test string, the parameters corresponding to the centroid 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. This subjective model estimation is presented formally in Algorithm 1.

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

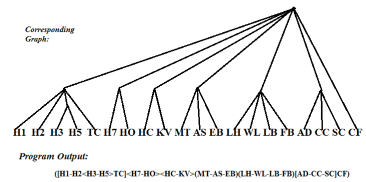


Figure 2: Regionalization *Subject 3*: The figure represents the ordred tree algorithm output for this subject.

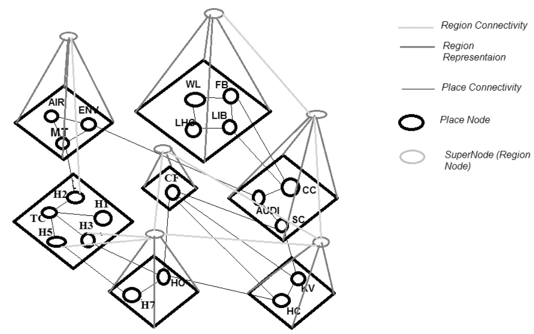


Figure 3: Focal Representation for *Subject 3*: Regions are defined based on previous figure. For a way finding task with H1 being the start point , this is the focal representation.

for testing it), and the similarity index is determined to validate the working of the model.

Results and Discussions

The aim of the experiments was to validate the computational model and to find out the trend in the tendency to support one navigation scheme over the other. While (M. J., A., and H.A. 2004) conjectured that way finding is a linear combination of all the three methods with equal weights, our experiments revealed a general tendency to favor 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, TC), (H7, HC, CF), (HC, KV), (MT, AS, EB) and (WL, LH, FB, CC, AD, SC, LB). On the other hand, *Subject 3* considered CF as a separate region all by itself. He also considered (CC, AD, SC) as a separate region while the rest were grouped as in *Subject 1*'s output. Figure 2 shows the output of the ordered tree algorithm for *Subject 3*, and Figure 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 subregion 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

[6]Please refer to original paper for a detailed description of the procedure.

[7]One of the 20, usually the hall of residence they resided in, to better approximate real way finding scenario of shopping etc.

[8]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. The Jaro-Wrinkler metric 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 (Cohen, Ravikumar, and Fienberg 2003) assert that it is one of the best string metrics available.

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 H1 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, AS 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.

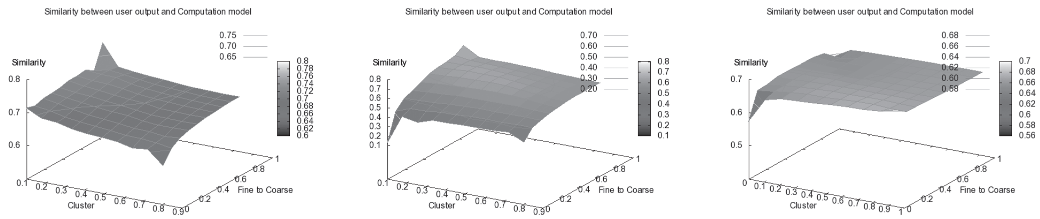
The experiments helped in finding out the parameters for each of the subjects individually, on a subjective basis. For the ten subjects, the optimal average α lied between 0.4 and 0.9, while β and γ were in the interval (0.1, 0.6) and (0.0, 0.3) respectively, with the average value for the three over all the subjects being 0.55, 0.35 and 0.10 respectively. The average string similarity index for each subject lied between 0.76 and 1.0 (for perfect match), with the average over all the ten being 0.84.

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 4(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 (refer to Table 1). From Figure 4(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 [LH, 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.

(M. J., A., and H.A. 2004) 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 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 4(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 ((Bailenson, Shum, and Uttal 2000)).

Explanation We might begin to interpret this trend in the following way. 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 This, added with the ten-



(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*

Figure 4: 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.

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*

dency 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. 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.

Conclusion and Future Work

In this work we proposed a stochastic memoryless process approximation to human navigational behavior in familiar environments. The claims the model was based upon were validated through literature survey and experiments on human subjects. We looked into the three heuristics from (M. J., A., and H.A. 2004), and in the process, found evidence that contradicts the authors' claim that all three are followed equiprobably. We found that subjects preferred the *fine-to-coarse* method over the other two. 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 within 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. For want of any better available heuristics that are well received and validated, we have employed only the three proposed by (M. J., A., and H.A. 2004). However, assuming that the hierarchical nature of spatial memory for way finding tasks would not be contested, when a new and valid heuristic needs to be implemented, it can easily be incorporated in the present model through minor tweaks in the edge-weights.

At this point, we have only considered familiar environments. However, it is possible to encode initial regions in terms of a clustering algorithm, and hold great potential for guiding the design of information for new spaces, or other tasks of relevance to spatial navigation. Furthermore, while we have assumed the process to be memoryless, it might so happen that based on how much time one spends at a target, the next heuristic selection might be dependent on the present one, leading to a first-order Markov process. This angle has not been investigated in the present work, and might lead to further advancements in understanding human behavior.

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