UNDERSTANDING TOPOGRAPHICAL DISORIENTATION: A SIMULATION

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INTRODUCTION

Topographical orientation is the ability to orient oneself within the environment and to navigate through it to specific destinations [1]. On the other hand, Topographical disorientation generally refers to the family of deficits in orientation and navigation in the real environment.

Recent studies have suggested that specific structures in the human brain such as the parahippocampal gyrus, the parietal cortex and the temporal cortical areas play an important role in topographical orientation [2-4].

It is generally agreed that in normative wayfinding, humans employ a number of different wayfinding strategies, including landmark recognition, route learning and map-like representations [5-6]. These strategies can be used independently or in combination. The choice of the strategies to follow may depend on the developmental age of the individual, his familiarity with the environment, the task to be accomplished, the detail level of the environment and how the environment was introduced to the individual.

Although there is a wide range of studies on the causes and implications of topographical disorientation as mentioned before, there is limited research on the navigational patterns followed by these patients. Epstein et al. [7] have reported one case study in which a patient with topographical disorientation may present a navigational behaviour that resembles a random walk when they are asked to reach a goal departing from a start point in a building that the patient is familiar with.

In this paper is developed a simulation tool to understand the navigational patterns and behaviour of an individual with topographical disorientation, based on the errors that this patient might make while navigating in an indoor environment. The proposed simulation is used as a tool to achieve a better understanding of these navigational patterns and assess possible problems that individuals with topographical disorientation might be experiencing in real life situations.

METHODOLOGY

<u>Representation of a building as a connected graph</u>

The building structure was represented by a connected graph in order to capture the complexity of map representations. The connected graph provides a simplified representation of the areas that are physically connected.

This approach has been adapted from previous studies in the same area [8-9]. Specifically, in this work we adapted the scheme used by Belkhous et al to create a connected graph [9], reducing the complexity by using a single node per room opposed to a node per door. Therefore, to create a connected graph from a floor plan a node is placed in each room and at every decision point on the floor plan. A decision point is a physical space where a navigational decision has to be made (i.e. turning, continuing straight ahead, entering a room). Each node is labeled with a unique number for identification purposes.

Once all the required nodes have been placed on the floor plan they are connected by edges. Two nodes will be connected if there is a physical, navigable connection between the two nodes (for instance, a hallway or an open door). Each edge is assigned a cost value which is related to its length. The edge shape must adjust to the physical constraint of the structure (i.e. they should follow the curvature of hallways). In this way the cost will physically represent the distance traveled by the patient (that can be related to the time taken to navigate along the edge at a constant speed).

To have an accurate relationship of distance between the nodes in physical space and the graphical representation of this distance by an edge, this edge must adjust to the shape of the physical constraints of the structure of the building (i.e. they should follow the curvature of a hallway).

In this way, a weighted connected graph that represents the structure of a building is constructed.

Data structure associated to the connected graph

In order to process the information provided by the connected graph generated with a simulation program, the information contained in the connected graph must be stored in a data structure that can be accessed by common programming languages.

A connection matrix is generated using a text file in a Comma Separated Values (CSV) format. The file contains the same number of rows and columns. The interconnection information for each node will be stored in both a row and a column; for instance, information on how node 3 interconnects will be stored in both row 3 and column 3. In this way the interconnection information relating nodes 3 and 4 will be stored in the cells (3,4) and (4,3), and both cells will contain the same value. The value of each cell of the matrix will be the cost associated with the edge connecting those two specific nodes. If there is no specific interconnection between two nodes, a value of -1 is stored, which will be interpreted as *infinity*. The value of the distance of a node to itself will be stored as -1 as well.

The dichotomy of value storage in the matrix, (x,y) and (y,x) is physically representative and eliminates the need to provide the nodes in a specific order.

Route selection

Chown et al [6] state that two subsystems are involved in visual cognition, called “contour” and “location” subsytems. Both subsystems are combined to account for landmark identification and direction selection respectively as used in wayfinding tasks. Chown et al. also propose that both subsystems work in a connectionist fashion, whichs resonates with the idea of connected graphs, and also state that navigation can be achieved with just one of these systems, being the second used in a more advanced stage of process of wayfinding than the first as it is used when the user is familiar with the environment.

In order to simulate a system based on direction-selection only, we decided to use existing well established routing algorithms. Provided that we have a connected graph representing the environment, we can use an existing routing algorithm such as the Dijkstra algorithm, or A* or D*, to calculate the shortest path between two interconnected nodes on the graph. The Dijkstra algorithm is a graph-theoretic method [10] that has been widely applied for routing packets in communication networks, and is used by routers interconnecting communication networks being implemented in the 'Open Shortest Path First' (OSPF) routing algorithm [11-12]. It is also commonly applied for routing humans [13], mobile elements (i.e. robots) and virtual or simulated subjects in labyrinths and maps [8, 9, 14].

The Dijkstra algorithm was therefore selected to simulate a human navigation direction selection based system. The algorithm was programmed in PERL, which offers a simple language conducive to data management.

Disorientation simulation

The Dijkstra engine programmed will calculate the most efficient route to follow in the connected graph representing the building. As stated previously, an individual with topographical disorientation presents a walking pattern that resembles a random walk when he is asked to navigate from a start point to a destination inside a building. Therefore, we decided to assign a Probability of Confusion P_C, where $0 \leq P_C \leq 1$ which reflects the likelihood of the individual making a wrong decision with regards to the next path to follow at each decision point. A value of $P_C = 1$ will generate a random walk pattern. A value of $P_C = 0$ indicates a perfectly oriented individual.

After defining P_C for the individual, he is requested to walk from a start point to a destination in a building represented by a connected graph as described before. The process is as follows:

1. Define the value of P_C for the individual, $0 \leq P_C \leq 1$.
2. At each node traversed by the individual, obtain a random value R from a uniform distribution, where $0 \leq R \leq 1$.
   a. If $R < P_C$ at that node, the patient will chose randomly to follow any of the edges available at that node.
   b. If $R \geq P_C$ at that node, the best route to follow from that specific node to the destination will be calculated using the Dijkstra’s algorithm, and the individual will move to the next node as calculated.
3. The process is repeated at each node from step 2 until the individual reaches the destination node.

Experiment design

Five virtual individuals with different values for P_C were defined. $P_C = 0$, $P_C = 0.25$, $P_C = 0.5$, $P_C = 0.75$ and $P_C = 1$. A virtual building was defined and its structure was mapped to a connected graph using the method described previously. The building created is shown in Figure 1.

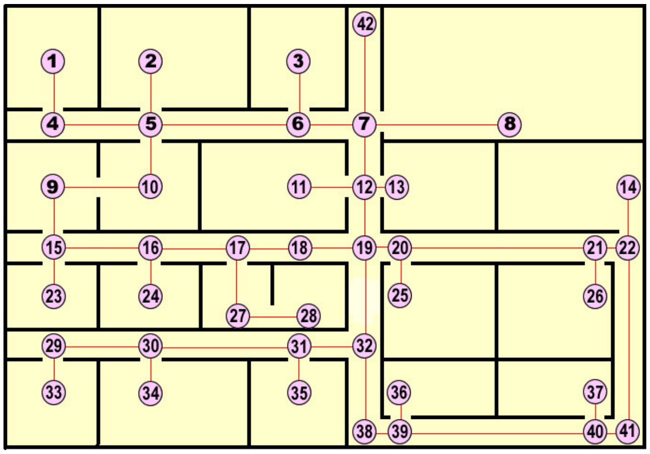

Figure 1: Synthetic building designed.

Each virtual individual was asked to walk through the building 25 times from node 10 to node 37. The number of nodes traversed and the distance traveled were recorded.

RESULTS

Estimates for the number of nodes traversed and the distance traveled by each of the individuals with varying levels of confusion are reported in Table 1. The probabilistic distribution of the parameters recorded was similar to a gamma distribution. Therefore, the data were fitted to gamma distribution in order to obtain the location and variability estimates.

Table 1: Location and variability estimates of the distribution for the number of nodes traversed and distance traveled by individuals with different P_C values. Numbers in parenthesis indicate the data variability.

P_C	***Nodes traversed***	***Distance traveled***
0	10 (0)	974 (0)
0.25	14.2 (3.2)	1336 (322)
0.5	21.9 (7.5)	2043 (717)
0.75	53.3 (24.4)	4700 (2114)
1 (random walk)	281.9 (238.0)	24784 (20900)

The paths followed by individuals with a) P_C = 0 (no confusion), b) P_C = 0.25, and c) P_C = 0.5 are depicted in Figure 2. The distances traveled by each patient were a) 974, b) 2192 and c) 2282.

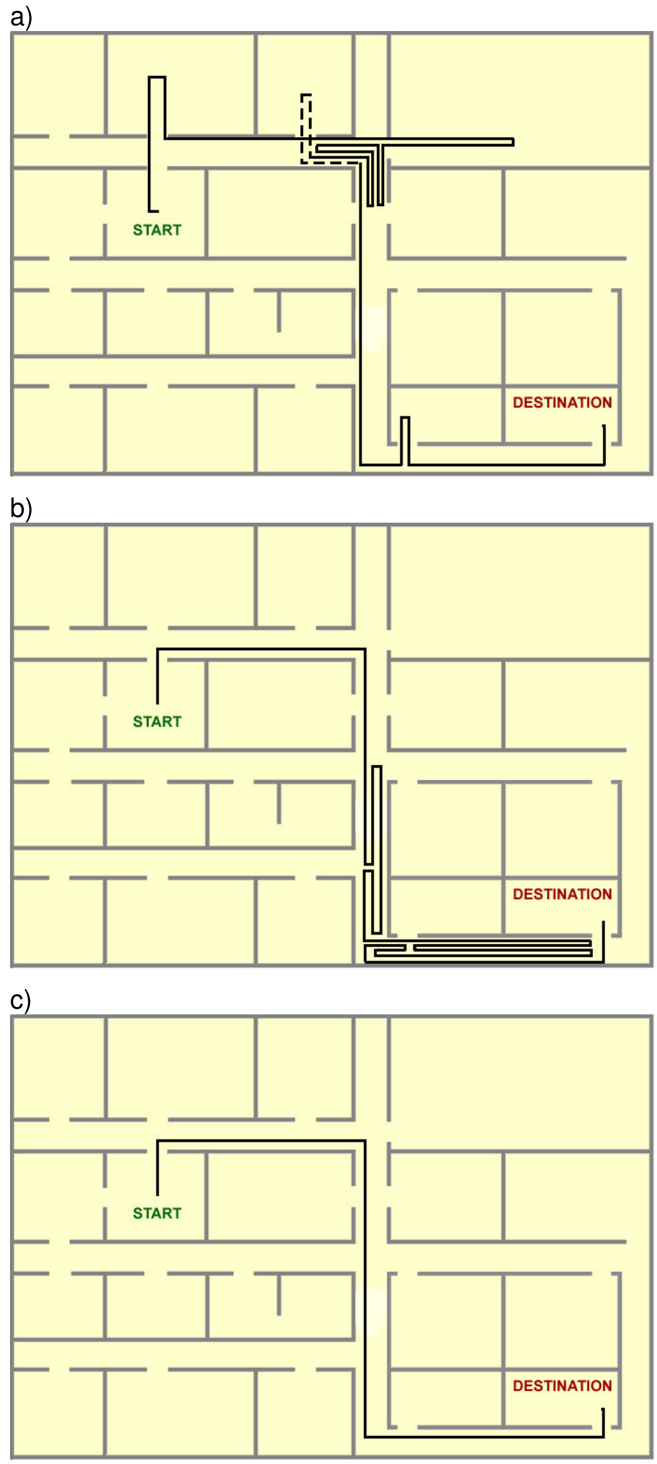

Figure 2: Routes followed in the first run of the 25 runs for the patient with a) P_C=0, b) P_C=0.25, c) P_C= 0.5.

DISCUSSION

These results show that the distance traveled by an individual with P_C = 1, who is in fact performing a random walk in search of the destination room, is more than 25 times the distance traveled by an experienced oriented individual for the specific experiment designed. If we compare the random walk results with the route that might be followed by an individual experiencing topographical disorientation as suggested by Epstein el al [7]. This would imply that an individual with severe topographical disorientation would need at least 25 times longer than an individual traveling at the same constant speed. This time may be even higher if we account for the time that a disoriented individual may require while making navigational decisions. This can result in frustration experienced by an individual with topographical disorientation.

Figure 3 depicts the exponential relationship between the distance traveled by the individuals and their level of confusion P_C.

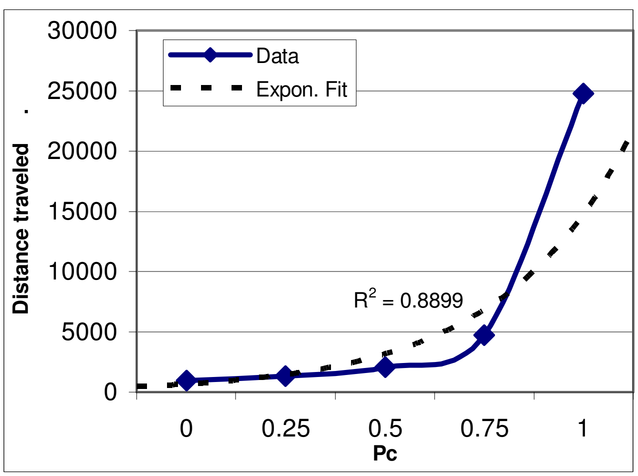

Figure 3: Probability of confusion (P_C) Vs. Distance traveled.

CONCLUSIONS

This work shows initial steps towards the simulation of the navigational patterns followed by individuals experiencing different levels of confusion, which could be related to different degrees of topographical disorientation. This tool may help in understanding the navigational patterns followed by individuals experiencing topographical disorientation and could reveal possible problems and challenges that might be econtered in real life situations. This simulation tool enables modeling of multiple scenarios in a short time and with no inconvenience to patients. Further development and validation of this tool is required.

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