A Network Analysis Approach to Understand Human-wayfinding Problem

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Abstract

We have considered a simple word game called the word-morph. After making our participants play a stipulated number of word-morph games, we have analysed the experimental data. We have given a detailed analysis of the learning involved in solving this word game. We propose that people are inclined to learn landmarks when they are asked to navigate from a source to a destination. We note that these landmarks are nodes that have high closeness-centrality ranking.

Introduction

Human navigation has been a topic in spatial cognition for quite some years now (Aginsky, Harris, Rensink, & Beusmans, 1997; Hart & Moore, 1973; McDonald & Pellegerino, 1993; Moore & Golledge, 1976). To understand how humans explore a complex environment, Moeser (Moeser, 1988) conducted an experiment and observed how nurses learned to traverse in a hospital building which had a very complex structure. Aginsky et. al., (Aginsky m. fl., 1997) proposed two strategies that humans adopt in learning to navigate, they infer from their experiments that humans follow either a visually dominated or a spatially dominated strategy to solve a route-learning problem. Basakya et al., (Baskaya, Wilson, & zcan, 2004) explore spatial orientation and wayfinding behavior of newcomers in an unfamiliar environment. Passini (Passini, 1984) has proposed that in wayfinding problem, one learns whatever is necessary and sufficient to achieve a goal.

In recent years, another type of complex environment has attracted scientific research, namely *complex networks*. It has been known for a long time that most real-world networks belong to the type of so-called *small worlds* (Watts & Strogatz, 1998), i.e., that they have a small average distance and that it is thus easy to reach each node within only a few steps. This has first been demonstrated by a classic experiment by Milgram (Milgram, 1967) in which he asked the participants to send a letter via acquaintances to some person unknown to them. Most of the letters reached their target within only a few steps. This basic finding was also reproduced by Watts et al., (Sheridan Dodds, Muhamad, & Watts, 2003) using emails. Since the experimental results were quite clear, only decades later Kleinberg finally asked the question of **how** people are essentially able to **find** the short paths in a small-world without any further information (Kleinberg, 2000b, 2000a). Since there are potentially many paths of short length, this is indeed not totally obvious. In his model Kleinberg assumes that each target is associated with a location, given by geometric coordinates. In this setting he proves that only a restricted type of small-worlds enables people to navigate within them efficiently. In a follow-up paper, Simsek and Jensen (Simsek & Jensen, 2008) show that a similarly efficient navigation can also be achieved in a model based on degree and homophily. To our knowledge, none of these models have been tested with real humans.

The word-morph game presents a well defined navigation problem in a complex network: given two words w_1, w_2 of the same length, one is asked to find a sequence of words from w_1 to w_2 such that each successor differs in only one letter from the predecessor. Fig. 1 shows some examples of feasible solutions for the word pairs $(BOY, PER), (CAR, SHY), (AXE, NUT)$, and (TRY, POT). Note that these are just one of the many possible solutions.

In this work, we combine the word-morph game problem with a network analytic approach to understand how humans navigate in these complex networks. In the given setting, a navigator is neither equipped with geometric information as in Kleinberg's model, nor is there a notion of homophily between words that is meaningful for solving the puzzle. Thus, the navigation strategy cannot be described by any of the models sketched before. The simple setting allows to directly identify the strategy by which people learn to navigate in a complex network. We can show that they quickly identify so-called *landmark words* which they use most frequently in their navigation. We can also show that these landmark words have a central position in the complex network, leading to a

$BOY-PER$	$CAR-SHY$	$AXE-NUT$	$TRY-POT$
BOY	**CAR**	**AXE**	**TRY**
|	|	|	|
BAY	*CAT*	*APE*	*TOY*
BAT	*PAT*	*ACE*	*TON*
CAT	*PET*	*ACT*	*TIN*
CAR	*SET*	*ANT*	*SIN*
PAR	*SEE*	*AND*	*SIT*
|	*SHE*	*AID*	*PIT*
PER	|	*BID*	|
	SHY	*BIT*	**POT**
		BUT	
		|	
		NUT	

Figure 1: Exemplary word-morph games.

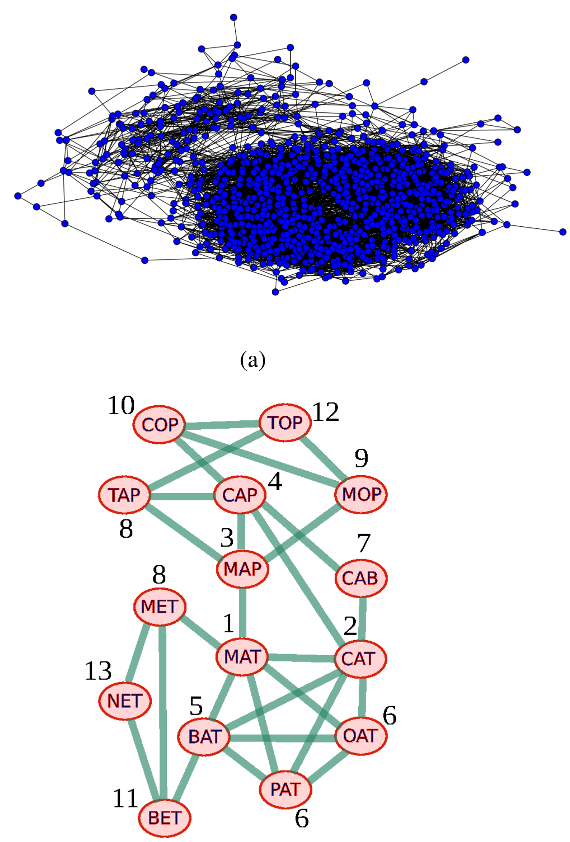
direct correlation between the network's structure and human navigation in it. Once these landmark words have been detected by a navigator, the time she needs to navigate from one point to any other point decreases significantly. The approach of our paper can be easily generalized to observe more specific questions about how humans navigate in complex networks as we will discuss in the summary. The paper is organized as follows: Sect. gives the necessary definition, before the experimental setting is explained in detail in Sect. . The results of the experiments are discussed in Sect. , followed by a discussion of related work in Sect. . We finish with a conclusion in Sect. , which discusses possible generalizations of our network analytic approach to the human wayfinding problem.

Definitions

A graph $G=(V,E)$ is composed of a set of nodes V and a set of edges $E\subseteq V\times V$, with $|V|=n$ and $|E|=m$. A *way* between two nodes u and v is any sequence of edges $(e_1,e_2,\ldots,e_k)$ with $e_1=(u,x_1),e_2=(x_1,x_2),\ldots,e_k=(x_{k-1},v)$. A *path* is a way with no repeating nodes. The length of a way is defined as the number of edges in it. A *shortest path* between two nodes u and v is a path with length l, such that, every other path between u and v is of length greater than or equal to l. Two nodes are said to be *connected* if there exists a path between them. The *distance* $d(v_1,v_2)$ between any two nodes is defined as the length of a shortest path between them, or set to ∞ if there exists no path between them. Any maximal set of pairwise connected nodes is called a *component* of the graph. Let Σ be a set of letters, and Σ^* be the set of all possible concatenations. Let $L\subseteq\Sigma^*$ be some language and L_k denote the set of all words with the same number of letters k. For a given L and k, one instance of a *word-morph game* consists of two words $(start,end)\in L_k\times L_k$. A *solution* of this game is any sequence of words $start=w_1,w_2,w_3,\ldots,w_k=end$ such that any two consecutive words differ in exactly one letter. E.g., for the pair (CAR,SHY), the following sequence is a solution:

$$(CAR,CAT,PAT,PET,SET,SEE,SHE,SHY).$$

The rules of the word-morph game defines a natural relation $\simeq_R$ on all words in L_k, i.e., regarding the rules, any two words v,w in L_k are related if they differ by exactly one letter. Thus, $(L_k,\simeq_R)$ defines a graph on the words in L_k, which we call the *word-morph network* $G(L_k)$ on L_k. In the following, L_k will be the set of all three-letter words in English, as defined by the Oxford dictionary (Catherine & Angus, 2005), and $G(L_3)$ is the respective graph. $G(L_3)$ is shown in Fig. 2(a), a part of the full network is shown in Fig. 2(b).



(a)

(b)

Figure 2: (a) The word-morph network $G(L_3)$ composed of all three-letter words in English. (b) A part of $G(L_3)$ together with the ranking of the nodes, as defined by the closeness centrality.

A *centrality index* is a real-valued function $C:V\rightarrow\mathbb{R}$ on the nodes (Brandes & Erlebach, 2005). The intuition is that the higher the value of this function, the more central this node is for the network. There are various indices; in this article we use the so-called *closeness centrality* (Sabidussi, 1966) $C_C(v)$, which is defined as the reciprocal of sum of the distances of v to all other nodes w:

$$C_C(v) = 1 / \sum_{w \in V} d(v,w)$$

For any given graph, a centrality index can be used to define a ranking on the nodes, by sorting the nodes non-decreasingly by their centrality value. Fig. 2(b) shows the ranking of 15 nodes in a subgraph of $G(L_3)$.

To understand the exploration and navigation of humans in a complex network, we conducted a series of word-morph games with 20 different participants. The experimental setting will be described in the following.

The Experiment

The experimental setting: The experiment was conducted on 23 participants (16 men and 7 women). 3 participants (all men) gave up before playing the first ten games. The 20 participants whose data is presented in our analysis are all those who completed exactly 65 games. The average time that participants took to play all the games was 233 minutes. Participants played the game without taking any break in between. All 20 participants were graduate students of the age group $20-25$ of the Indian Institute of Science. None of them knew the game before hand. From the list of all 967 three-letter words contained in the Oxford dictionary (Catherine & Angus, 2005), each participant P_i first selected the words she knew. This set is denoted by $V(P_i) \subseteq L_3$, and the respective graph is denoted by $G(P_i)$. After that, the game was explained to the participant and we asked her what her initial strategy will be to solve the game (Question I). After the first 15 games we asked whether any kind of difficulties arose while playing the game (Question II). After playing another 50 games, the participant was then asked whether their initial game solving strategy was useful (Question III).

Creating the word-morph instances: Every participant's graph $G(P_i)$ had a biggest component, which was almost the same as the graph except for 5 to 10 words. Exact statistics are provided in the results section (Sect.). Smaller components were either isolated nodes, or isolated edges. Only the biggest component was retained and the rest were deleted from $G(P_i)$ - for every i. We shall henceforth mean, by $G(P_i)$, the biggest component of the graph.

All 65 word pairs were chosen to be distinct. For the first 15 games, word pairs (w_i, w_j) were choosen such that each of the word pair's $d(w_i, w_j)$ was 5. The distance between words was increased by 2 units every 10 games thereof. This was easily possible, as the *diameter* which is defined as $max\{d(u,v) : u,v \in V\}$ of the graphs $G(P_i)$ on an average was 12.3.

Information logging and post-processing of the data: For each participant P_i her selected vocabulary $V(P_i)$ was saved and $G(P_i)$ computed. For this graph, the closeness centrality was computed for all nodes and their rank determined by sorting the words accordingly. For each of the 65 game instances, we stored the word pairs that was given to the participant and her solution. Time was recorded for 10 participants. Participants entered their solutions via an interactive computer program. They were not allowed to use any writing aids.

Results

We will first discuss the properties of $G(L_3)$ together with the graphs $G(P_i)$. We will finally describe the results concerning the actual game solving process.

General properties of $G(L_3)$

Table 1: Properties of $G(L_3)$ and $G(P_i)$

Property	$G(L_3)$	Max	Min	Avg
Nodes in graph	967	626	306	446.8
Nodes in Biggest component	967	619	297	438.3
Number of components	1	12	5	7.1
Diameter	9	14	10	12.3
Average path length	3.54	4.29	3.69	3.97
Average degree	16	11.8	7.6	9.6

In Table 1, the second column contains the properties of $G(L_3)$, while the third fourth and fifth columns respectively contains information on maximum, minimum and average values of the $G(P_i)$, for all $1 \leq i \leq 20$.

The first observation is already astonishing: while the first 10 games took our participants 10 to 18 minutes per game, after around 15 games, they became reasonably faster. Their solving time dropped to 2 minutes per game. It furthermore dropped to a mere $\frac{1}{2}$ a minute after 28 games. Fig shows the time taken vs the game number. Time taken is averaged over 10 participants.

Participants found it very difficult to solve the first few games. It can be easily seen from Fig. 3 that the time spent to solve the instances were significantly higher on the first 10 games as compared to that of the successive games.

Analysis of the answers to the three questions

- Answer to QI: 100% of the participants answered that the strategy which they thought will work, was to first find a word which matches one letter of the final word, then starting from that one to find a word which matches the final word in two letters.

- Answer to QII: After 15 games, 95% of the participants said that they were finding it extremely difficult to solve the game.

- Answer to QIII: 100% of the participants felt that the strategy which they answered in QI did not work and that they found a new strategy: "Navigating through certain words made the game very easy to solve."

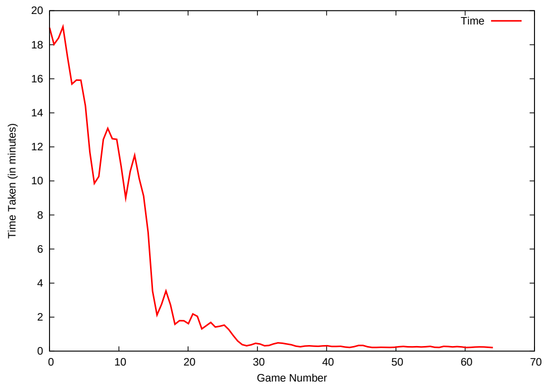


Figure 3: Average time taken per game in seconds vs number of games played.

The answers show that the subjective impression after 15 games is that the game is still difficult to solve. It is very interesting to note that 100% of all participants chose the same initial strategy and that all of them changed to a different one finally. They also state that they used a subset of words as via media to navigate through the network. In the following we will show how to determine these words for each participant by an analysis of the solutions. A deeper analysis regarding the relationship of this set to the structure of the word-morph network will then reveal that this set is an absolutely non-random selection.

To illustrate, let us consider a few games played by one of our participants, *Ms. Hilda*. In 46 out of the total 65 games that Ms. Hilda played, she used at least one of the words *HIT*,*OAT*, and *AID* to navigate from any given word to any other word. Below are some of the word-morph games that Ms. Hilda played. Note the usage of the *landmark word AID*:

EGO AGO ADO ADD AID BID BAD BAY BOY TOY TOE WOE
SAY BAY BAD BID AID ADD ADO AGO EGO
BAY BAD BID AID ADD ADO AGO EGO EGG
ASS ASK ARK ARM AIM AID BID BAD BAR EAR
THY TOY BOY BAY BAD BID AID ADD ADO AGO AGE

We noticed that participants used certain landmark words repeatedly to navigate on the network. To understand how these words are used to navigate in the network, we will now introduce two definitions concerning the trajectory of a single solution. Let $S(P_i,x) = \{w_1,w_2,\ldots,w_k\}$ be the solution of participant P_i for the x-th game as defined by the word pair (w_1,w_k). To each word, we assign its closeness centrality rank in $G(P_i)$. Consider, e.g., the word pair $(CAP-AWE)$ and its solution by one of the participants in which each word is assigned its rank:

CAP(59)-SAP(23)-SAY(33)-WAY(73)-WAR(125)-OAR(116)-OAK(163)-YAK(183)-YAM(158)-DAM(99)-DAY(48)-DRY(167)-TRY(178)-THY(171)-THE(156)-SHE(166)-SEE(114)-BEE(90)-BYE(157)-EYE(180)-EVE(195)-AVE(204)-AWE(210)

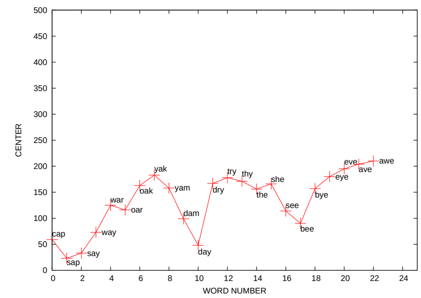
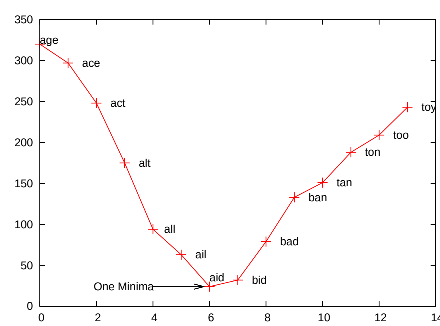
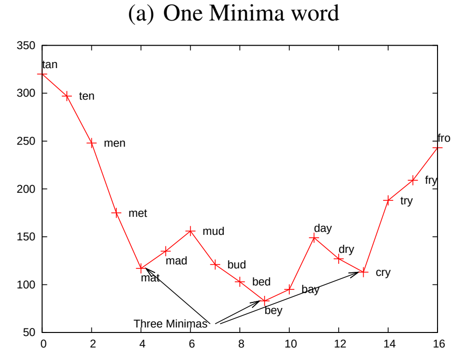


Figure 4: A rank plot for the game $(CAP-AWE)$ where the rank is computed with respect to the word-morph network of the according participant.

Fig. 4, shows the rank of the i-th word in the solution vs i, i.e., its trajectory through the word-rank space. Such a plot will be called a *rank plot* in the following. Note that such a path can contain local minima, i.e., words whose closeness centrality rank is lower than that of both neighboring words in the solution. We call such a word a *minimum word* in the solution. The path shown in Fig. 5(a) contains only one minimum word (*AID*), while the solution shown in Fig. 5(b) contains three minima words (*MAT*, *BEY* and *CRY*).



(a) One Minima word



(b) Three minima words

Figure 5: Minima of a path

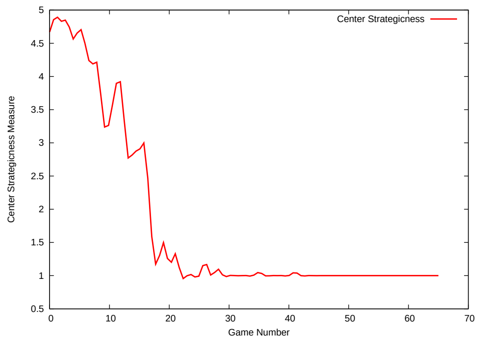


Figure 6: Plot of average centerstrategicness vs the number of games played

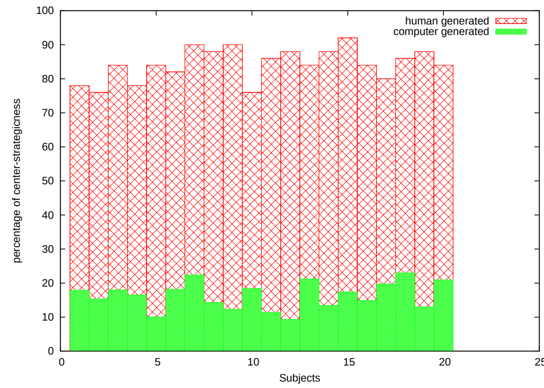


Figure 7: Percentage of center-strategic solutions of each participant (subject) P_i of all 65 solutions (red bars) in comparison with the expected percentage of center-strategic paths in a random walk scenario in $G(P_i)$.

Center-strategicness of the path: The number of minima words in a solution is called the *center-strategicness* of the path. Thus, the center-strategicness of the path in Fig. 5(a) is 1, whereas the center-strategicness of the path in Fig. 5(b) is 3. We call a solution *center-strategic* if it has exactly one minimum word. The solution depicted in Fig. 5(a) is *center-strategic* whereas the solution depicted in Fig. 5(b) is not *center-strategic*.

The absolutely surprising result is that after 22 games out of 65, each and every single participant only uses center-strategic paths.

Main Inference: Fig. 6 gives us a very important inference, we have plotted mean of the *center-strategicness* of the *paths* which the participants took Vs game number. The curve hits 1 at 22nd game and remains 1 henceforth. Put in simple terms, after playing a few games, participants used only *center-strategic paths*.

The sudden decrease in average solving time is tightly coupled to the identification of a set of landmark words. This set of words is then used in a center-strategic way to navigate efficiently through the network.

Note that this strategy is indeed very efficient: instead of learning the whole network which would potentially allow to find the shortest path for any two given words, participants learned only a few important landmark words and they first navigated to these landmark words and then reached the final word. Interestingly, the paths chosen in that way were considerably longer than the shortest paths. Path length deviation of a participant P_i is denoted as $\Delta(P_i)$ and is defined as the average of the ratios of actual path length is to shortest path length of all 65 games. The set $\{\Delta(G(P_1)), \Delta(G(P_2)), \ldots, \Delta(G(P_{20}))\}$ has minimum 1.22, maximum 1.37 and an average of 1.254. Which signifies that the paths taken by the participants were far from being the shortest path.

To understand whether the peculiar structure of the word-morph network in general or the word-morph networks of the single participants in specific caused this effect, we computed the average fraction of center-strategic paths in the following way: Given a word pair (w_1, w_2), we compute random paths of length less than or equal to 20, using the random walk procedure in which every path is explored with the same probability. For example, out of 18,197 random paths between *AXE* and *NUN* only 3,128 paths turned out to be center-strategic. The fraction of center-strategic paths between *AXE* to *NUN* is thus 17%.

For each participant P_i we computed this fraction for each of the 65 word pairs in her respective graph $G(P_i)$, and averaged over the fraction. Furthermore, for all 65 solutions we computed the fraction of center-strategic solutions for each P_i. Fig. 7 shows for each participant the fraction of center-strategic solutions and the average fraction of center-strategic paths of all possible solutions. It can be clearly seen that the human navigator chooses center-strategic paths with a significantly higher probability than the virtual random walk procedure. This result rules out the fact that the structure of the network itself dictates the usage of center-strategic paths.

Related work

Of special interest to us is the work by Moeser (Moeser, 1988), in which he reports on results of a study conducted in a five-storey hospital which had a very complicated structure. It was noted that the student nurses did not learn new ways to navigate better even after two years of their stay in the hospital. The reason for this is well explained by the work by Passini, which says that humans learn only what is necessary and sufficient to achieve a goal (Passini, 1984). We believe that these necessary and sufficient things which people learn in order to navigate in a complex network like the word-morph network, are the nodes with a high centrality-ranking.

Allen (Allen, 1997) has proposed certain important issues in production and comprehension of route directions by attempts to way-find a destination. He suggests that technological innovations aimed at providing verbal information to assist wayfinding activity be incorporated within a framework focused on the ecology of wayfinding behaviour. Maguire et al., (Maguire, Burgess, & O'Keefe, 1999) discuss how Complexity and content of the environment affects navigation success apart from the sex and age of the participant. Golledge (Golledge, 1995) has analysed the kind of paths that people select in virtual vs real environment. Guidice et al., (Giudice, Bakdash, & Legge, 2007) propose that the similarity in learning and wayfinding behaviour observed between verbal and visual conditions indicate that the spatial representation built up from verbal learning is functionally similar to that developed from visual learning.

Conclusion

As far as we know, this study is the first study that aims at understanding the navigation of humans in virtual complex networks. With a simple approach and the help of network analysis we gathered convincing evidence how humans explore such a network in a way that is sufficient (but not necessarily optimal) for navigation in it. We showed that the efficiency with which the network is explored increases drastically after the identification of a set of landmark words. Furthermore, these words belong to a network analytically determinable set of the most central nodes in the according word-morph network. Our work has thus direct implications for the design of complex connection or transport networks used by humans. By using the representation as a network, we can predict which parts of the connections will be used most and thus need special attention in the design phase to, e.g., make sure that streets are broad enough or that a lift's or tram's capacity is sufficient.

In general, our simple approach of asking participants to find a set of paths in a given network allows for very controllable experiments. Due to the simple experimental setting, the paths chosen by a participant give direct evidence of her mental map of the network. We envision different variants of the basic way-finding problem in which nodes or edges are associated with additional information. One idea is to test Kleinberg's navigation hypothesis for humans by asking them to navigate through an artificial network where nodes are associated with geometric coordinates. Another experiment could explore how participants react to a blockage, i.e., a (temporal) removal of those landmark nodes they identified beforehand. Furthermore, a longer series of games would also be interesting: we suspect that after a while participants will finally explore the whole network by searching for short cuts. This could eventually turn into a personality test, based on the intuition that outgoing, innovative people are more likely to step out of the known paths sooner than others. In summary, we hope that the basic approach underlying this study opens a new field in the analysis of human wayfinding in complex networks.

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