UNIVERSITY OF SOUTHAMPTON

FACULTY OF MEDICINE, HEALTH AND LIFE SCIENCES

School of Psychology

Strategies of Human Spatial Cognition: Cognitive and Behavioural Trade-offs

by

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Thesis for the degree of Doctor of Philosophy

January 2009

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

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STRATEGIES OF HUMAN SPATIAL COGNITION: COGNITIVE AND BEHAVIOURAL TRADE-OFFS

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Human spatial strategies are heuristics that allocate cognitive and behavioural resources for navigation tasks. These spatial strategies help the individual optimize its interactions with the surrounding space through functional trade-offs between the memory costs of planning routes and the cost involved in actually travelling that distance. These trade-offs result in visitation patterns of initial exploration of the space and subsequently determine navigation efficiency. The purpose of this thesis was to observe, identify and describe patterns of spatial exploration, understand the trade-offs and strategy optimizations they encompass and empirically quantify their performance both in physical and abstract (i.e., virtual, computational model and informational) spaces.

The first study presented a novel methodology of identifying spatial exploration patterns based on cluster analyses in a physical room and measured navigation efficiencies according to a spatial strategy trade-off between memory demands and distances travelled. Two exploration patterns were found that determined subsequent navigation. Explorers with an 'axial' pattern were more memory efficient and followed a fixed route sequence to find objects; whereas 'circular' pattern explorers were more distance efficient with less overall travel on more flexible route choices.

The following two studies used the same experimental design and methodology to further examine the effect of spatial constraints on cognitive and behavioural resource optimization, specifically looking at the issues of exploration on forced routes in a physical space and in an effortless virtual space. In both spaces, the efficiency trade-off observed in the first study was affected. On the one hand, forced physical exploration reduced navigational control and overwrote individually preferred spatial strategy optimizations. On the other hand, effortless virtual exploration resulted in preference towards optimization of cognitive resources over distances travelled. These presented examples of spatial environmental biases.

Following the three behavioural studies, an agent-based model is presented. It formalized the main hypothesis of this thesis that human spatial cognition is optimized by spatial strategies via simulating exploration patterns with memory and distance heuristics. The model also replicated the behavioural findings and allowed further insights into the trade-off observed in the first study.

The lessons learnt from the model and the three behavioural studies were then tested in a practical e-learning environment. The application of the theoretical findings provides further understanding into human spatial cognition. In the study, three different spatial layout website designs were analysed for their navigational and learning utilities both immediately and 2-weeks post exploration. This web based navigational study revealed the role of spatial control in long-term retention and other cognitive benefits. Together these studies present important insights to human spatial cognition and its implications.

Contents

List of Tables

List of Figures

Declaration of Authorship

I, Tamás Makány declare that the thesis entitled Strategies of Human Spatial Cognition: Cognitive and Behavioural Trade-offs and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was completed wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- parts of this work have been published as:

Makány, T., Redhead, E. S., & Dror, I. E. (2007). Spatial exploration patterns determine navigation efficiency: Trade-off between memory demands and distance travelled. *Quarterly Journal of Experimental Psychology, 60*(12), 1594-1602.

Makány, T., Engelbrecht, P. C., Meadmore, K., Dudley, R., Redhead, E. S., & Dror, I. E. (2007, March). *Giving the learners control of navigation: Cognitive gains and losses.* Paper presented at the International Technology, Education and Development Conference (INTED 2007), Valencia, Spain.

Makány, T. (2006). Optimality and cognition: Shortest paths and smartest brains. *Periodicals of Implicit Cognition, 4*, 1-6. Retrieved January 12, 2008, from http://www.implab.org/public/pic4.pdf

Signed: Makány Tamás

Date: 27th January, 2009

Acknowledgements

For all the support and encouragement during the years of my post-graduate research and especially during the preparation of this thesis, I wish to express a great deal of gratitude to a number of people and groups. First, thank you to the School of Psychology for funding my research.

Thank you to Dr. Anne McBride and the Animal Behaviour Clinic at the University of Southampton for providing space for the experimental room used in Chapter 2 & 3 and to Edward Wood for his help in the data collection. I am also thankful for Dr. Erich Graf and Dr. Alexander Klippel for lively discussions on cluster analysis.

Thank you to Jon Pyke for his enthusiastic work as a volunteer undergraduate research assistant in the Yellow Brick Road study (Chapter 3). He spent countless number of hours helping me with testing participants and analysing data and his talent for statistics was invaluable. Also thank you to Dr. Alex Furr for the visual design and to Luke Phillips for programming the virtual space in Chapter 4. For the e-learning study in Chapter 6, I am thankful for the collaboration of Paula Engelbrecht, Katie Meadmore and Richard Dudley.

The attendance at the 2006 Complex Systems Summer School, Santa Fe Institute, NM was my most valuable educational and networking experience. Having met there in the spirit of interdisciplinary research, I gratefully acknowledge the collaboration and friendship of the economist, Dr. Michael Makowsky, who coded the agent-based model in Chapter 5 and discussed the formalization of the *memory-distance* (M-D) hypothesis with me in great details.

Thank you to Dr. Matthew Parker and Carlos Galan-Diaz for proof-reading and peer-reviewing the final draft of this thesis. I am truly grateful for both of their insightful and thorough comments.

I wish to thank my fiancée, Julie Schiller for being so patient and supportive partner through the preparation of this thesis. I look forward to doing the same for you anytime in our future. And thank you to my mother and brother, Zsuzsánna Vajda and Balázs Makány, for their perpetual trust in me.

Finally, my special thanks go to my supervisors: Dr. Itiel Dror and Dr. Edward Redhead. They gave me guidance and support throughout all my research at Southampton. Thank you for helping me think critically and confronting me with the different levels of human cognition.

Preface

In December 2005, I visited a contemporary sculpture exhibition called *Embankment* by Rachel Whiteread in the Tate Modern Art Gallery in London (Figure 1). The huge installation was more of a labyrinth than a single sculpture that consisted of many hundreds of white plastered casts of differently shaped old cardboard boxes. The brochure described that they were "positive impressions of negative spaces", the casts preserved the features of the inside surface which were now turned inside out to form the walls of the labyrinth.

Figure 1. A corridor leading through the "negative space" at the Embankment sculptor exhibition created by Rachel Whiteread. ©Tate, London 2008.

I was intrigued by the creativity of the artist as I was wandering through this exhibition. Complex structures, configurations and geometry of the surrounding space are rarely in the focus of our everyday conscious examinations. Even in the most familiar environments, like in our homes, we tend to concentrate on the embedded content and not the structures. People, books, paintings, computers are much more prominent to our attention than how much empty space is left between the shelves and the sofa or what is the actual shape of our kitchen. It is only these special occasions, like this exhibition or designing a new home that make us wonder that our interaction with the environment might be much complex than what we thought.

In his book, *The Space Is the Machine*, Bill Hillier (1996) presents his theory of 'analytic architecture' that describes how the configurations in urban designs affect our social lives. Cities, streets and buildings are seen as dynamic patterns of interlinked networks that include us humans and determine our behaviours, feelings and actions, all through the symbolic language of spatial configurations. Incidentally, Hillier and his colleagues also realised the research potential of art galleries, when they conducted a study of how visitors utilize the space in the twin institute of Tate Modern, the Tate Britain, which is only a short boat cruise apart from one another on the Thames River. They found that aggregate movement flow of visitors correlated with the configuration maps derived from the physical properties of the gallery as people preferred to walk on visible and straight linear routes during their exploration. The authors argued that such movement patterns occur because people are reading space in geometrical and topological terms and these features determine navigation behaviours. A definite merit of analytic architecture from the perspective of cognitive psychology is that it reflects on the importance of the context in which the individual behaviour takes place. Hillier's approach demonstrates from a very practical perspective that people exist in meaningful environments and they are able to make sense of this 'common language of space' (Hillier, 1999). This interesting insight into the interaction between people and spaces, however, does not explain why are we so prone to the surrounding environment, and what are the basic principles that govern spatial navigation. To further investigate these issues, first I have to return to my own spatial experience at the Embankment sculpture exhibition in the Tate Modern. Although I was sure that the physical layout of white plastered casts of old cardboard boxes affected my movement patterns, it was less obvious whether other visitors would navigate the same ways or maybe some individuals would react differently.

As long as individuals are collapsed into statistically critical masses, patterns emerge in almost every aspect of life and complex systems research has already provided numerous examples of systematic regularities in nature and in human behaviour (Ball, 2006; Barabási, 2002; Csermely, 2006). A recent study, closely relevant to my visit in the gallery, from the team of the complex network researcher, Albert-László Barabási, analysed mobile-phone data and revealed a high degree of mathematical regularity in way people move around places in their daily lives (González, Hidalgo, & Barabási, 2008). Their results from a massive database of over 16 million registered spatial movements for 100,000 anonymous mobile-phone users showed that human mobility patterns can be described by a relatively few number of simple navigation rules or travel strategies. The strategies include time-independent travel distances and frequent returns to a few significant locations that are based on detailed statistical characterisation of individual trajectories. Based on this method, reliable predictions can be made upon the probabilities of finding an individual in any location within the entire space. In simple terms, it means that if the management of Tate Modern decided to surprise me at any particular time with a lifelong membership, now they have the required knowledge how to find me based on the data available from my frequent visits to the Gallery. Undoubtedly this mathematical approach of navigation has potentials way beyond the conventional boundaries of social science research (and of rewarding amateur art lovers with free tickets). However, the itching urge of turning such formulas into a profitable application might overshadow the confusion in the use of the very first word of Gonzáles et al.'s paper published in the journal Nature. *Understanding individual human mobility patterns* claims the title, despite the fact that the purpose and realisation of the article is a probabilistic description rather than a quest for comprehension. Readers skilled in mathematics are given a sophisticated research tool to understand how people behave in large groups and how they travel around spaces, but as the Editorial section (p. 698) of the same issue also noted, it provides no answer to the question why individuals navigate the way they do. The problem of particular individual events remains one of the most exciting challenges of future complex system and social sciences.

As I had been wandering around the exhibition for over an hour, semi-consciously (or perhaps over-consciously) aware of the 'big picture' of my spatial environment, I suddenly realised that I had forgotten to look at any of the plastered boxes from a close distance. I felt foolish that I had almost missed out the “positive impressions of negative spaces” as promised by the brochure. In fact, that would have been the perfect example of the famous ‘art museum problem’ coined by Holyoak and Thagard (1996; but originally posed by Foss, 1989) where the high cognitive demands of seeing most of an exhibition superficially can result in missing the details or relatedness of the individual items; like not paying attention to the inside out turned boxes that made up the whole of the Embankment sculpture. What went wrong? Why was I so selective in acquiring and processing information arriving from the environment? How did this limited spatial perception affect me in exploring the gallery? These were my immediate questions when I stepped close to examine the wall of the labyrinth.

Each and every white plastered cast box inside-out seemed very similar, even if they were all slightly different in size or shape. There were simply too many details to remember and after a short while I did what most of us would have done – I stopped. The process involved an intuitive decision (Kahneman, 2003) of my cognitive system, as it was quick and without too much consideration. There was a threshold in the amount of details that I was willing to learn from my immediate environment before I walked somewhere else. Herbert Simon (1979) argued that people are highly selective in their information acquisition and utilization due to their limited cognitive capacities. In addition, those few boxes that I was looking at represented only a fraction of the overall information; hence the available resources from my environment were also scarce. The fact, however, that I was able to decide when to stop exploring suggested that I used a *spatial strategy* that evaluated my information needs, my existing resources and the limitations from both the environment and of my own cognitive system. When I finally stopped exploring, I was perfectly happy to accept that I had learnt enough about the exhibited ‘negative spaces’. At that point, I felt satisfied with my visit to the Embankment exhibition in the Tate Modern and I was ready to go home.

The take away message from the art gallery on that day was that it takes more to understand human spatial behaviour than only measuring travelling distances or considering geometrical configurations. Visiting the Embankment labyrinth made me realize that the decisions about the space (e.g., which route to take? how much more to walk? or when to stop exploring an area?) are deeply interlinked with how the cognitive system allocates and optimizes its desired and available resources – both physically and cognitively. The nature of these strategy optimizations is not a well-studied area of spatial cognition research and it is a fascinating perspective for me to contribute to this field with the thesis.

Scope, Structure and Hypotheses

Scope

This thesis focuses on strategies of allocating cognitive and behavioural resources in human spatial cognition and how these determine navigation performance and efficiency. Humans, as adaptive intelligent agents, developed heuristic mechanisms to overcome the limitations of their environments and their own information processing capacity. These mechanisms relate to the minimal and most efficient use of resources for solving spatial navigation tasks are referred to as *spatial strategies* throughout the thesis. The definition sits on the shoulders of many interdisciplinary giants, including 'search strategies' in spatial learning (e.g., Downs & Stea, 1973; O'Keefe & Nadel, 1978; Thinus-Blanc, 1996), 'heuristic strategies' in game theory (von Neumann & Morgenstern, 1947), 'optimal foraging' in evolutionary ecology (MacArthur & Pianka, 1966; Stephens & Krebs, 1986) and 'information foraging' in human-computer interactions (Pirolli & Card, 1999). The present work aims to provide a valuable addition to these fields, not only with a novel empirical method for experimentally identifying spatial strategies but also with the integration of these different approaches into a coherent framework of cognitive psychology.

In general terms, the heuristic assumption underlying spatial strategies describes observed behaviour based on a set of strategies evolved to find the most likely way to reach a spatial goal. These strategies are not well-defined steps with clear predictable and guaranteed outcomes, rather statistical probabilities based on individual preferences and previous experiences. More specifically, those patterns of cognition and behaviour are considered the outcome of a spatial strategy that is likely to contribute to a successful completion of a spatial task. According to this definition, relying on salient landmarks could equally indicate a spatial strategy, such as following a well-learnt route, or searching unexplored spaces. The motivation for using the term in this broad sense is to reflect on the inherent trade-off involved in the human cognitive system that balances between cognitive demands and behavioural costs of an action (Anderson, 1991).

Spatial strategies represent dynamic and continuously changing interactions between the individual and the surrounding environment. The observable spatial behaviours, such as exploration patterns, route choices or landmark use are emergent properties of the underlying cost-benefit analyses of the cognitive system. Thus, it is important to emphasise that this thesis is not only concerned with describing the actual spatial behaviour, but also in revealing the organisation of the spatial strategies. Observed behaviour, for example the repeated use of a specific navigation route, is always interpreted in terms of a heuristic trade-off that can change its form with space and time. The primary purpose of this thesis is twofold. First, it aims to identify recurring patterns of human exploration and to understand the strategies of cognitive and behavioural resource allocation under different environmental constraints. Second, the empirical studies presented go beyond the identification and description of the observed spatial behaviour and discuss the underlying mechanisms of spatial knowledge acquisition and efficiency optimization.

The thesis focuses on individual agents performing search within their environment and does not explore social and other influence on the individual's cognition and behaviour. Although investigating the emerging group-level behaviour of collective search strategies increases the external validity of foraging studies (Goldstone & Janssen, 2005; Goldstone, Roberts, Mason, & Gureckis, 2008), it is not within the scope of the thesis.

Structure

The first chapter of this thesis presents a synopsis of the interdisciplinary research of spatial cognition focusing on the existing literature on strategies and cognitive optimization. It opens with a section introducing some of the building blocks of the field. These are core concepts and they are used throughout the thesis. After the basic definitions, the interactive relationship between the individual navigators and four different spatial environments is discussed. These are:

- physical space
- virtual space
- computational model space
- information space

The introduction than continues with an overview of different scientific approaches to optimal behaviour and performance. Finally, the chapter critically reviews the current understandings of spatial strategies.

The introduction and literature review is followed by five empirical studies (Chapter 2-6) exploring spatial strategies in different environments or experimental conditions. Although the chapters demonstrate a progressive line of research, whereby the conclusions of one chapter forms the basis of the next chapter, each study also represents an individual piece of research work intended to be published as an independent article. At the time of the final editing of this thesis, all five studies have already been published either in peer reviewed academic journals or presented at international conferences.

Chapter 2, published in *The Quarterly Journal of Experimental Psychology*, presents the development of a novel methodology, which is used in an experiment that identified two spatial strategies (axial & circular) for initial free exploration of space and their implications on subsequent navigation task performances (Makány, Redhead, & Dror, 2007). Exploration patterns of the participants were analysed in a square-shaped physical environment containing five identical boxes each hiding a distinct object. The aim of this experiment was twofold. First, it described the novel method for identifying spatial strategies. To this end, the detailed presentation of the classification algorithm provided a baseline methodology for further investigations in this thesis and spatial studies in general. Second, the experimental results were discussed in terms of navigation efficiency achieved by different optimizations focused on either the cognitive or behavioural resources.

Chapter 3 is a follow-up study on the first experiment; it investigated the effects of initially forced exploration on navigation where spatial strategies were determined by the layout of the physical space. Participants were first assessed for their preferred initial spatial strategies in a free and unconstrained exploration in an equivalent space as in the baseline experiment. Following a rearrangement of the objects within the room, participants then had to explore the transformed space on designated and constrained routes that either matched or conflicted with their individually preferred search strategies determined during their initial free exploration. The purpose of this study was to analyse how spatial strategies determined by the environment modify the optimal efficiency trade-off between cognitive and behavioural factors of spatial exploration and learning. A preliminary version of this work was presented at the *2008 British Psychological Society Annual Conference* in Dublin, Ireland (Pyke, Makány, Redhead, & Dror, 2008).

In Chapter 4, the allocation of cognitive and behavioural resources was analysed during the exploration of a desktop virtual environment that had an equivalent spatial layout as the baseline experiment in Chapter 2. Participants in this experiment could also freely explore and perform specific search tasks in the virtual space by visiting the photorealistic image of the same five objects as in the physical baseline environment. The optimality of the routes during these tasks was compared between participants. In contrast to physical space, where the locomotion of the whole body requires considerable behavioural resources, in a desktop virtual environment the cost associated is changed. This could result in a modification of spatial strategies and consequently a change in the performance indices. Therefore the aim in this chapter was to look at whether the same exploration patterns are found in the virtual environment as in the real space; and also to investigate if people allocated their resources similarly within the two environments. Preliminary results of this study were presented at the *International Conference on Spatial Cognition* (ICSC 2006, September) in Rome, Italy and it appeared in writing as part of the conference proceedings in the journal *Cognitive Processing* (Makány, Dror, & Redhead, 2006).

The fifth chapter of this thesis investigates the same issues but from a computational perspective, looking for converging evidence from different experimental approaches. The chapter presents an agent-based computational model simulating human spatial strategies discussed in the previous chapters. Spatial strategies were operationalised as simple heuristic strategies. In the model, an artificial agent explored five target locations situated on a two-dimensional square lattice designed to replicate the baseline laboratory setting. The agent chose her route according to a cost function that optimized behavioural utility that was a function of two complementary strategies; *Memory strategy,* which set the knowledge acquired about the environment and *Distance strategy,* which set travel distances. This simulation aimed to provide further understanding and testing of the hypothesis that humans optimize their spatial decisions in terms of trade-offs between cognitive and behavioural expenses. An initial model was published as part of the proceedings for the *2006 Complex Systems Summer School* at the Santa Fe Institute, NM, USA (Makány & Makowsky, 2006).

Although the main purpose of the thesis was to pursue the scientific research and to better understand spatial strategies, Chapter 6 applied the results from the previous chapters into a real world problem within the domain of learning in an information space. The application of the findings to a real world domain not only allows further testing and examination of the findings, but provides insights back to the theoretical findings. Borrowing the idea from information foraging that people search for information with similar exploration strategies as in physical spaces (Benyon, 2006; Pirolli, 2005), this chapter investigated human learning performances in three differently structured but equal information content e-learning layouts. The spatial structure of the information space, and the control that the learners had in exploring it, seemed to play a major role in determining mental representations and learning. The question in this chapter was what are the resources involved, and thus the gains and losses in allowing the learners to control their explorations in an abstract information space? In other words, how spatial strategy optimization takes place in e-learning? This work was presented at the *International Technology, Education and Development Conference* in Valencia, Spain. The full paper appeared in the INTED2007 Conference Proceedings (Makány, Engelbrecht, et al., 2007). In addition, this project was awarded the *University of Southampton Vice-Chancellor's Teaching Award* in 2007 for its outstanding contribution to university education.

Chapter 7 concludes the thesis and gives an outlook on the ongoing and future research. In this final chapter, the findings about spatial strategy optimizations are summarised and discussed in terms of their theoretical and practical relevance to spatial cognition research. This concluding chapter brings everything together to provide an overall view of what all the findings mean together. Specifically, in this chapter the main findings are categorized according to exploration pattern identification, spatial strategy optimization, efficiency trade-offs, environmental biases and navigational control. The chapter ends with a discussion of the impact of the current thesis, and suggestions for future work.

Hypotheses

To restate and summarize the main goals and hypotheses of this thesis it is useful to formulate research questions. These questions are generated before the experiments to frame and motivate them: the answers are intended to help describe and understand the psychological mechanisms involved in human spatial strategies under different environmental constraints. These questions are:

- How do people allocate their cognitive and behavioural resources when interacting with their spatial environment?
- How do spatial strategies predict navigational performance and efficiency?
- What is the role of the environment in spatial strategy selection?

The main contribution of this thesis is the *memory-distance* (M-D) hypothesis:

> *Human spatial cognition is optimized by heuristic spatial strategies that function as a trade-off between the cognitive memory costs of route-planning and the behavioural costs of travelling distances.*

Further chapter-specific sub-hypotheses are generated and addressed in the relevant chapters of the thesis.

Chapter 1: Literature review

Spatial Cognition: Definitions

Research on spatial cognition represents an interdisciplinary field of studies focusing on the acquisition, organisation, utilisation, and revision of knowledge about the spatial environment (Freksa, Habel, & Wender, 1998; Garling & Golledge, 1993; Montello, 2001; Thinus-Blanc, 1996). Spatial cognition is part of the human cognitive system that allows people to adapt optimally to their spatial environments, understand spatial properties of objects and relations, and essentially to navigate from one place to another. However, before going into details of these processes, it is necessary to define some basic terminology.

The term *spatial* is principally used in an extended geographical sense pertaining, or relating to anything in space. *Space* denotes an area or location, including not only physical spaces but also virtual or abstract environments. For spatial cognition research, any location that the cognitive system can interact with is therefore a potential ground for investigation. This includes laboratory rooms, mazes, urban metropolises, computer-generated games, websites, the Internet, fantasylands or even our dreams. Parts of spaces that are highly relevant within the process of navigation are called landmarks or cues. However, most landmarks are relative in a sense that they are defined in relation to other reference points or landmarks (Evans & Garling, 1991).

Navigation is goal-directed and oriented travel through space (Montello, 2001). As mentioned earlier, this may not require real physical movement between spaces, but it can happen in virtual worlds or between webpages. A key feature of navigation is paths, upon which linear travel can occur, such as roads or links. However, navigation may or may not happen exclusively on paths, as travellers can cross through open fields or type in URLs directly. Routes are therefore representing linear patterns of movements either on formal paths or beyond them. Navigation routes will be in the centre of analysis in the thesis, because they characterise spatial cognition.

A cognitive plan of routes is a prerequisite for travelling distances during navigation. This plan represents an internalised knowledge that allows inferences about the spatial features and relations of the external world (Gallistel, 1990). Spatial information about locations or objects can be integrated into the cognitive system in two different ways, depending on the dominant frame of reference (Berthoz, 1991; Hart & Moore, 1973; Klatzky, 1998; Levinson, 1996). When the new information is relative to the person's own location (e.g., "the mountain is in front of me"), it is called egocentric or viewer-centred representation. In contrast, if the referencing is independent from the observer and relative to other external places or objects (e.g., "the mountain is north of the river"), it is referred to as allocentric or object-centred. These two frames of reference are essential underpinnings of spatial cognition, both in terms of how the information is processed and how it is updated into previously existing knowledge. However, their real functions have been recently questioned (see for example, Burgess, 2006; Iglói, Zaoui, Berthoz, & Rondi-Reig, in press; Nico & Daprati, in press; Wang et al., 2006).

Now that the key terms have been specified, areas of current research will be discussed. The study of spatial cognition includes several research topics, out of which, three main paradigms are reviewed here: (1) spatial orientation, (2) spatial learning, (3) wayfinding and navigation. Although these processes are described individually, they are all part of an integrated spatial knowledge system. Therefore, an integrated view of these paradigms is needed with an understanding of their main questions. As this thesis will touch upon all of these three topics, I review some of the relevant research questions and debates in the following sections.

Spatial Orientation

Spatial orientation, or awareness of the surrounding space, is our general ability to perceive, understand and represent the spatial environment around us (Hunt & Waller, 1999). This includes both spatial perception, the ability to determine spatial relations, and spatial visualization, the ability to manipulate complex spatial information (Linn & Petersen, 1985). For example, during the process of orientation, information from our current location within the environment and the relative location of other elements are processed and continuously updated into a spatial knowledge system (Wang et al., 2006).

Orientation ability has been studied most frequently in terms of individual differences of processing spatial information (Millar, 1994; Ungar, 2000). For example, in a recent study by Fortenbaugh, Hicks, Hao, and Turano (2006) participants were required to orient themselves in a virtual forest. The results showed that good performers relied more on their internal spatial representations and less on external visual information than poor performers. This suggests that people with good orientation skills are more effective because they are better able to respond to the loss of available external visual information than others.

Although most people can use cross modal senses in spatial awareness, sighted humans dominantly rely on vision when orienting in space (Millar, 1994). However, in situations where vision is restricted or absent, other modalities, such as proprioception or haptic senses, could compensate for the shortage. Blind people, for example, are essentially using the same information acquisition and organisation mechanisms to deal with their spatial environment as sighted people, despite the lack of the additional benefits of seeing distant spaces (Ungar, 2000).

Another process of spatial orientation is the updating of newly acquired information into existing knowledge systems (Cheng, 1986; Cheng & Newcombe, 2005; Wang et al., 2006; Wang & Spelke, 2002). Early work by Cheng (1986) provided evidence that rats use geometric information to reorient themselves in an ambiguous spatial situation. Rats were put into a rectangular arena with food presented in one corner. Throughout the testing phase the arena was rotated from trial to trial and the rats had to relocate the place of reward within the enclosure. The rotation made the internal inertial cues irrelevant for the search; consequently the only available cue was the geometric information of the rectangular arena. The study revealed that rats mixed the diagonally opposite corners, even if other feature information was provided which disambiguated these locations. However, these errors were systematic in a sense that only these similar corners were chosen by the rats, showing that the animals represented the geometric properties of the arena. Accordingly, Cheng proposed the idea of a geometric module in the rat's brain that encodes such information for reorientation (see Fodor, 2001 for details on modularity).

The geometric module contains the broad shape, symmetries, principal axes, angles, and other geometry related information that is used together with non-geometric (feature) landmarks for spatial orientation and learning (Cheng, 1986; Gallistel, 1990). A recent debate raised the question of whether animals use local features or global geometric cues to recover from disorientation (Cheng & Gallistel, 2005; Pearce, Good, Jones, & McGregor, 2004; Tommasi & Polli, 2004). A local matching strategy would use angles, wall lengths or stored propriocentric information of previously travelled routes. In contrast, a global matching would make comparison on the basis of overall shape parameters: for example, the symmetry axes. Experiments with rats (Pearce et al., 2004) and pigeons (Tommasi & Polli, 2004) showed that animals trained in a rectangular test environment made systematic errors when they were relocated into a disorienting environment that went through non-Euclidean shape transformation (i.e., changed into a kite or parallelogram-shape). These experiments concluded that animals were adapting only local matching of angles or wall length. Conversely, Cheng and Gallistel (2005) argued that a parsimonious explanation requires both global and local encoding of geometrical information. According to their analysis, although the animals were not matching global shape congruence, they were still orienting on the basis of determinate global processes, such as the principal or symmetry axes of the space.

The question of whether local or global matching happens in reorientation and spatial updating leads the present discussion towards the investigation of the applied frame of reference in spatial representations. On the one hand, purely egocentric models argue that spatial memory is always relative to the observer and that the updating process is taking place continuously and dynamically with movement (Simons & Wang, 1998; Wang et al., 2006; Wang & Spelke, 2000, 2002). For example, when participants had to reconstruct their original locations after a change in their viewpoint, an increase in the number of objects negatively affected their performance (Wang et al., 2006). This result was explained by an increased memory cost of spatial updating that allowed only the most relevant – egocentrically related – objects to be updated. These egocentric models imply a highly unsteady state of spatial representations, which could result in a "fragmented knowledge" of our environment. These fragments are continuously changing – similar to the image of a kaleidoscope – as the person moves within the space.

On the other hand, two-system models support the idea that allocentric representations, centred on the external objects, are present in parallel to, and complimentarily to the egocentric ones (Burgess, 2006; McNamara, 2003; Mou, McNamara, Valiquiette, & Rump, 2004; Nadel & Hardt, 2004). The allocentric encoding system contains enduring relative location information of spatial objects that is more rapidly and easily accessed from all potential viewpoints. The neural foundations of the two-system models are described in brain imaging studies reporting differential brain activation for tasks that involved either allocentric or egocentric frames of reference (Burgess, Jeffery, & O'Keefe, 1999; Hartley, Maguire, Spiers, & Burgess, 2003; Maguire et al., 1998; Parslow et al., 2005). Activation of the right hippocampus is observed, for example, when participants orient in allocentric navigation tasks, whereas inferior parietal areas become more active when they follow arrows in front of themselves (Maguire et al., 1998).

Spatial Learning

Going beyond orientation, spatial learning takes the momentary information acquired during orientation and consolidates it in memory. Research in this branch of spatial cognition is focused on the process of acquisition and the nature of such representations. Traditional approaches of spatial learning proposed that the environment is instantly represented in the form of a global mental isomorphism – a cognitive map (Gallistel, 1990; Morris, 1981; O'Keefe & Nadel, 1978; Poucet, 1993; Thinus-Blanc, 1996; Tolman, 1948). According to Tolman (1948), a “tentative, cognitive-like map of environment” (p. 200) is established in the brain and mental computations on the spatial array precede the execution of the navigation behaviour. This mental ground would allow us to represent multiple objects in relation to each other, and to compute novel shortcuts and routes between them (Morris, 1981; O'Keefe, 1991). The subsequent and continuous updating of the emergent spatial features (i.e., landmarks) makes the map a highly flexible mental tool for various navigation tasks. Once the space is represented, the navigator is able to make detours or shortcuts on unexplored areas of the environment (Chapuis & Scardigli, 1993; Gould, 1986; O'Keefe & Nadel, 1978; Thinus-Blanc, 1996).

For example, Gould (1986) trained honey-bees to fly from their hive to a food source (site A). The trained foragers were then put in a different site (site B) within their foraging territory, which could not be seen from site A, and therefore no close landmark could be directly approached. Nevertheless, all the bees successfully returned to the food source (site A); moreover, they returned in a straight line. This result supports the existence of a cognitive map, as the previously known area was used to deduce the novel direction information (Pearce, 1997).

A more recent experimental technique, the star maze, was designed to investigate spatial learning in rats and in particular whether or not these animals used a global representation (allocentric frames) of the environment (Rondi-Reig et al., 2006). The results showed that almost a fifth (19%) of the rats learnt in a purely allocentric representation, and the majority (60%), in mixed allo- and egocentric frames that required, at least partially, a cognitive map. These and other similar findings from behavioural neuroscience with animals and humans (for a recent review, see Kumaran & Maguire, 2005) suggest that cognitive maps are useful conceptual tools for explaining mechanisms of spatial learning.

The cognitive map approach has been often criticised from a behavioural economy point of view (Chamizo, 2003; Mackintosh, 2002; Pearce, 1997; Prados & Redhead, 2002). The most commonly raised point is why it is necessary to learn a complex, holistic map representation, when simply remembering a sequence of a limited number of landmarks and turns is sufficient to navigate effectively. Once an animal has learnt a particularly useful source of information for its navigation, it is very unlikely to attend to further cues, even if they are equally useful (Pearce, 1997). For example, in a simple learning experiment, rats were trained in a radial maze with a sandpaper-padded floor in one arm that contained the food. Even if other extramaze cues were available, the results showed that the salience of the landmark (i.e., sandpaper floor) blocked the learning of other cues, suggesting that no holistic cognitive map could have developed (Chamizo, Sterio, & Mackintosh, 1985). As summarized by Prados and Redhead (2002), the findings demonstrate that most of the observed spatial learning phenomena can be explained with associative and attentional processes, including blocking, overshadowing, latent inhibition, or cue competition.

The debate on the nature of representations – not only in the spatial domain, but also with regards to other fields such as the theory of mind or mental imagery – is yet to be resolved (see Byrne & Bates, 2006 for a recent review). Nevertheless, the focus of spatial learning research has shifted to a novel, integrative approach, and the emphasis is now on the development and enrichment of spatial knowledge, which is essentially continuous and dynamic.

One early theory of spatial knowledge formation proposed three levels of learning about the external space: landmark, route, and survey knowledge (Siegel & White, 1975). Initially, relevant landmarks are learnt and exist independently from other representations of locations or objects (egocentric frame). Acquisition and recognition at the landmark level takes place through perceptual learning and matching. Next, as the learner becomes more familiar with the environment, and repeatedly follows certain routes, the sequence of actions will be remembered. This route knowledge or procedural information is the second stage, relating to where landmarks are linked together within familiar routes. Route knowledge is derived directly from the experience of navigating the represented route. On the route level, distance estimations and relational inferences become available between previously acquired landmarks. Finally, survey knowledge represents the configurational relations between the landmark and route levels. This relates to the mental topography of the space, as it includes locations, relational and geometric information, which creates global, viewer-independent (allocentric), map-like knowledge.

Although Siegel and White's (1975) theory seems closer to cognitive map explanations, recent research by Foo, Warren, Duchon, and Tarr (2005) showed that even survey knowledge could be inaccurate and non-Euclidean (i.e., does not keep the rules of our experienced everyday geometry). This is because even the most well-learnt spatial representations are under dynamic reorganisation by being momentary, relying on view-specific perspectives and selectively acquiring environmental information (Foo et al., 2005; Wang & Spelke, 2002). Consequently, they cannot be the representational basis for a static topographical cognitive map. This evidence demonstrates that although people are able to construct a global representation of the space, they prefer to update their knowledge constantly via simpler learning processes from the lower levels (landmark or route).

Once again, this dynamic updating of spatial information is an important aspect in the learning process. This continuous change in the overall state of the cognitive system is led by informational enrichment (Clark, 1997; Kelso, 1995; Spencer & Schoner, 2003; Wang & Spelke, 2002). Kelso (1995) concludes that "learning changes not just one thing, it changes the entire system" (p. 173). In the light of these dynamic theories, it can be argued that the debate on the nature of spatial relation representation is misleading, as the two competing approaches describe other ends of the same process. Cognitive maps and associative spatial learning interpretations are not mutually exclusive, but they target different levels of spatial knowledge acquisition and representation.

Navigation and Wayfinding

The third research topic within spatial cognition is navigation and wayfinding. Representative studies emphasise the travel element in spatial behaviour; that is, navigators, after exploring and processing the available spatial information, plan, decide and execute a behavioural action (Chen & Stanney, 1999; Lynch, 1960; Passini, 1992; Thinus-Blanc, 1996).

There are three related processes here to clearly define: exploration, navigation and wayfinding. *Exploration* is an active and flexible information acquisition during the initial encounter with a novel environment that involves spatial orientation, spatial learning and travelling. During exploration, spatial features of the environment are organised and encoded into a dynamically updated spatial knowledge representation in the order of their encounter (Thinus-Blanc, 1996). In contrast to a free exploration, *navigation* emphasizes goal-directedness as a purposeful action of "determining and maintaining a course or trajectory from one place to another" (Gallistel, 1990, p. 35). Such behaviours include directed searches, target finding trajectories, aiming or guidance. Finally, during *wayfinding* multiple locations are visited according to a planned sequence, usually on a larger spatial scale (Franz & Mallot, 2000). In many cases, wayfinding is used as a synonym to navigation in a complex environment of more than one target locations. Planned urban environments offer natural research settings for wayfinding research (Denis, Pazzaglia, Cornoldi, & Bertolo, 1999; Golledge & Stimson, 1997; Hillier, 1996; Y. O. Kim & Penn, 2004; Lynch, 1960; Passini, 1992). These studies confirmed that spatial representations are organised along the same basic elements as built physical environments: paths (or routes), landmarks, nodes, districts and edges (Lynch, 1960).

Theoretical models of navigation and wayfinding claim that there are three distinct cognitive processes in complex spatial behaviour: cognitive mapping, decision-making, and decision-execution (Chen & Stanney, 1999; Passini, 1992). Chen and Stanney (1999) integrate these steps into their wayfinding model: first, individuals explore spatial features from their environment and represent it on a cognitive map. Once an integrated spatial knowledge system makes spatial inferences available, navigation action plans are developed in order to fulfil the requirements of the task. Following an evaluation process a route decision is made. In the final step, the selected action plan is transferred into a physical navigational behaviour. Factors that might be influencing this hierarchical wayfinding process include previous experience (e.g., familiarity effect), search strategy, individual differences (e.g., map reading ability, field dependence), motivation and environmental structure (e.g., street layout).

Section Summary

Spatial cognition is an interdisciplinary field of research dealing with the acquisition, organisation, utilisation and revision of knowledge about the spatial environment. The section began with basic definitions, which will be used throughout this thesis. Following these definitions was a review of traditional and recent approaches, debates, and some of the results from three main fields of spatial cognition: orientation, spatial learning and wayfinding. Although the focus of the research questions is slightly different in these fields, the separation is highly arbitrary as the studies are closely interrelated. Consequently, there are common themes that emerged in this section including dynamic spatial updating, spatial knowledge representation, and organisation of the spatial behaviour. In the second chapter of this thesis, an empirical investigation will be presented that addresses some of these themes. More specifically, individually preferred behaviours of spatial knowledge acquisition in a novel environment will be analysed. However, before that, the next section of the introduction will discuss the unique characteristics of different spatial environments.

Spatial Environments

Dynamism in the Environment

The external spatial environment constantly changes. Human cognition has answered this challenge by developing dynamic internal representations (Clark, 1997; Kelso, 1995). These mental structures accommodate the flow of new information acquired by spatial cognition. Helbing, Farkas and Vicsek (2000) argued that any individual in this flow is conditioned by two factors: internal (personal aims and interest) and external (perception of the situation and environment). In other words, internal representations of the environment are dynamic patterns of transient goals and unverified navigation plans. Both are subject to change as a result of spatial explorations. Thus, the dynamism of a spatial environment is the interaction between the constantly changing external resources and their internal representations.

Helbing, Molnár, and Keltsch (1997) presented an example of this interaction with the evolution of spontaneously emerging walking path trails in open spaces. A commonsense observation tells us that people when crossing a park have the tendency to follow previously trodden routes even if those are not the most direct ones. As people walk on these organically evolved routes, the grass becomes thinner and it becomes more reinforcing to walk on them. This demonstrates the dynamic interaction between the external environment (trodden routes) and internal factors (route-following tendency). When Helbing et al. measured how these evolved routes on a university campus compared with the mathematical shortest routes, they found systematic deviations from the optimum. According to the results of their computer simulations, spatial trail systems represent a compromise between directness to a target and the internal tendency of people to follow existing paths. The authors argued that modelling similar spatial situations, where constraints such as a budget limit on the total trail length matter, the best compromise can be found between economy and efficiency. Spatial foraging experiments with animals (Cramer & Gallistel, 1997; Menzel, 1973) and humans (Goldstone & Roberts, 2006; Pyke et al., 2008) also support this concept of spatial optimization between travel and memory costs.

The general principle behind self-organised trail systems and other similar phenomena, including media popularity (Gladwell, 2000) or academic citation networks (Börner, Maru, & Goldstone, 2004), is that “activity often begets more activity” (Goldstone & Roberts, 2006, p. 44). Studies in complex behavioural systems emphasise the collective aspects of spatial searches (Goldstone & Ashpole, 2004; Goldstone, Roberts, & Gureckis, 2008; Goldstone, Roberts, Mason, et al., 2008; Gureckis & Goldstone, 2006). These include peer presence and *stigmergy* – the mechanism by which resource allocations between collective foragers are coordinated (Grassé, 1959 as cited in Bonabeau, 1999). When other foragers are also present in a dynamic social environment, the individual search strategies are affected by the strategies adopted by these others. Group members, in order to optimize individual foraging efficiencies, could either choose to follow their peers (cooperation; see Greene, 1987) or avoid previous solutions (competition; see Lundberg, 1988). These group mechanisms are biologically hard-wired and they do not require significant cognitive resources, consciousness or even direct peer-to-peer communication. In human trail systems, stigmergy occurs when early travellers change the environment and subsequent travellers reinforce these changes by using the same initial paths (Goldstone & Roberts, 2006). Notice the interactive dynamism in collective spatial environments, as peers both change individual strategies of each other and the resource distributions of the environment. As a further point, stigmergy often happens within the behaviour of the individual. Hiking in the forest on a hidden path that we have once accidentally marked with our footsteps is one example.

On this last note, there are some important considerations when applying group behaviour principles, like stigmergy, to spatial cognition. Stigmergy results in adaptive behaviour without a need for mental planning, behavioural control, spatial memory or a specific goal, whereas spatial cognition involves orientation, learning and wayfinding strategies to a desired target (see previous section). Predictions on collective behaviour are probabilistic and in most cases refer to large populations. Such an approach is problematic for treating individual differences explicitly. Although in general the claim that “individuals rarely solve important problems in isolation from one another” (Goldstone, Roberts, Mason, et al., 2008, p. 278) is valid, the change of focus from one level of explanation to a higher level could lead to what is termed as “infinite regress” in philosophy. Ignoring the results from controlled laboratory experiments of the individual navigator and only explaining the collective spatial behaviour is what Dennett (1981) (within the context of complex cognition) would call the “loan of intelligence”, which has to be repaid somewhere else. Instead, the investigations of collective search behaviour should aim to complement and not substitute cognitive science and other complex system approaches to understand spatial strategies. Explanations on both the macro (group) and micro (individual) levels need to attempt to answer the same underlying question about how people allocate their resources when interacting with their dynamic spatial environments. Moreover, it is a common finding in network studies that the basic rules are the same regardless of which level of explanation they are applied (Barabási, 2002; Csermely, 2006). In spatial cognition, these rules are the strategic optimizations of resource allocation between the individual and its environment (that could include other individuals as well). What seems to be more crucial in understanding complex behavioural systems, like spatial cognition, is that the acquired information from the surrounding environment must be structured in relation to existing constraints (i.e., individual spatial representations) (Kelso, 1995). However, before discussing the actual optimization processes, I will focus on some key characteristics of the spatial environments discussed in the thesis.

Physical Spaces

The physical world around us encapsulates an enormous level of complexity in spatial and conceptual relatedness between its elements. People move through physical spaces every day to explore locations, routes, objects and other people for their desired resources. Adaptive exploration and exploitation of these spatial resources require the navigator to enrich and formulate mental representations of this space continuously. Acredolo (1981) made the distinction between small-scale and large-scale physical environments based on whether the space is open for immediate and visual apprehension or navigational displacement is needed to explore its content. A small-scale environment usually refers to the immediate physical space around the body, whereas large-scale spaces are often more complex built structures or open-field areas. This distinction not only reflects on physical visibility, but also on the related behavioural and cognitive action spaces. Small-scale environments are for reaching the goal or manipulating other egocentric relations, and the cognitive planning aspect of global environmental layouts is more apparent in large-scale spaces (Gouteux & Spelke, 2001).

An advanced methodology for measuring the spatial properties of physical spaces and their consequences to human living is *space syntax* (Hillier, 1996). This approach provides accurate and predictive information on how navigators utilise spatial information and travel in complex built networks (e.g., buildings, urban grids, parks, etc.). In addition, space syntax is able to quantify specific features of spatial complexity that seem to have great impact on how people move within their urban environment. For example, the intelligibility measure of the cities provides information of street linearization on an aggregate level. An intelligibly structured, linearised system improves the performance of human navigators in terms of their spatial wayfinding decisions (Conroy-Dalton, 2003). In an experiment, participants were tested in two virtual urban layouts that differed only in terms of their intelligibility. In the highly intelligible layout, blocks of houses were organised such that they created linear avenues and smaller but relatively straighter streets. The low intelligible layout included the same number of blocks and similar arrangements to the high intelligibility layout, but the avenues and streets were ragged by some slightly repositioned buildings blocks. Participants found the highly intelligible urban layout easier to navigate and they performed more efficiently compared to the low intelligible layout (Conroy-Dalton, 2003). This finding supports the claim that an optimal route depends also on the physical properties of the system. Thus in relation to navigation and wayfinding, spatial syntax research established that humans rely mostly on the geometrical and topological properties of the space in their navigation decisions and much less on metric measures (Hillier & Iida, 2005).

Another common experimental method to measure spatial behaviour in a physical space is to compute the proportions and the frequencies of the visited areas (Hills, Todd, & Goldstone, 2008; Makány, Redhead, et al., 2007). This usually involves overlaying a grid that covers specific single units of navigation (e.g., squares, steps or node visits) and counting cell visitations (see Figure 2). These measurements provide indications on both the size of the explored (and cognitively processed) area and the total physical effort that the individual navigator took during the behaviour. A more detailed explanation of this methodology will be provided in Chapter 2.

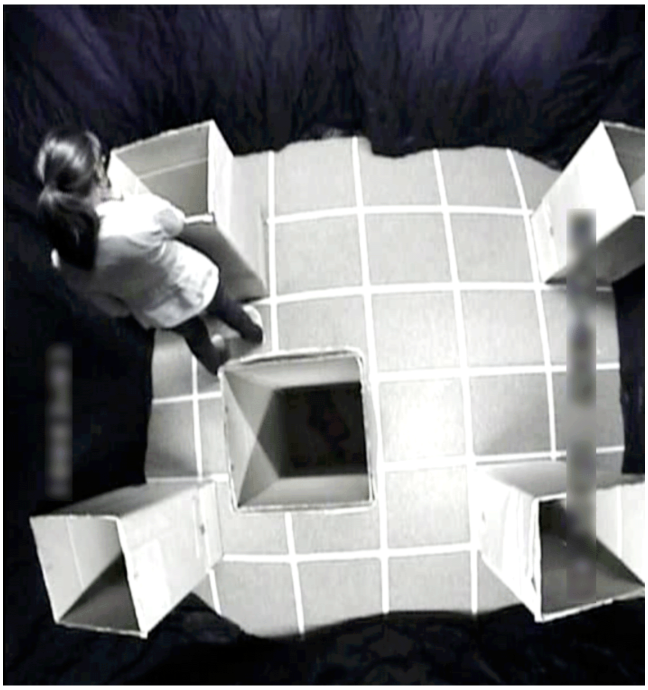


Figure 2. Physical space used for a spatial experiment recorded from a bird-eye-view perspective in Makány, Redhead, et al. (2007).

Abstract Spaces

Abstract spaces are non-physical environments created by, for example, virtual simulations (Tarr & Warren, 2002), hyperlinked websites (Benyon, 2006), internal cognitive representations (Hills et al., 2008) or semantic knowledge networks (Steyvers & Tenenbaum, 2005). The biological and cognitive mechanisms of spatial searches in these abstract spaces are analogous to those in the physical ones (Benyon, 2006; Hills, 2006; Hills et al., 2008). Hills et al. (2008) brings three examples to support this argument: information foraging (Pirolli & Card, 1999), decision heuristics (Todd & Gigerenzer, 2000) and evolutionary biology (Hills, 2006). I will discuss the first two approaches in more details later in this thesis. According to the biological evidence, the same dopaminergic processes are responsible for goal-directed behaviours and attention in many tasks. Based on this evidence, Hills et al. assumed that generalized search strategies operate during tasks of both physical and abstract environments. Furthermore, the authors found a priming of resource exploration and exploitation strategies between environments. Their participants were tested in a physical and in an abstract space for their spatial search performances. In the first task they had to navigate in a two-dimensional space, and in the second task they solved four-letter memory anagrams. The results showed priming across the two domains, as the individual search strategies were the same between tasks. A similar, but weaker spatial transfer was found in our laboratory when participants were found to be better at navigating in a physical room after exploring the spatial layout within a virtual environment than controls (Pyke et al., 2008).

Virtual Environment

Virtual environments (VE) are one of the most commonly used abstract spaces for spatial cognition research especially in studies related to spatial knowledge acquisition from navigation through an environment (Ijsselsteijn, 2004; Maguire, Burgess, & O'Keefe, 1999; Péruch & Gaunet, 1998; Waller, 2005). VE are computer-generated simulations of real or imaginary physical spaces represented either on a computer screen or in a more complex immersive setting. The different technologies and interfaces that enable users to interact with VE provide opportunities to observe and study human behaviour in precisely controlled, ecologically valid yet inexpensive and reproducible circumstances (Galan-Diaz, Conniff, Craig, Laing, & Scott, 2006; Tarr & Warren, 2002). For an illustration of a desktop-based VE used in a spatial learning experiment, see Figure 3.

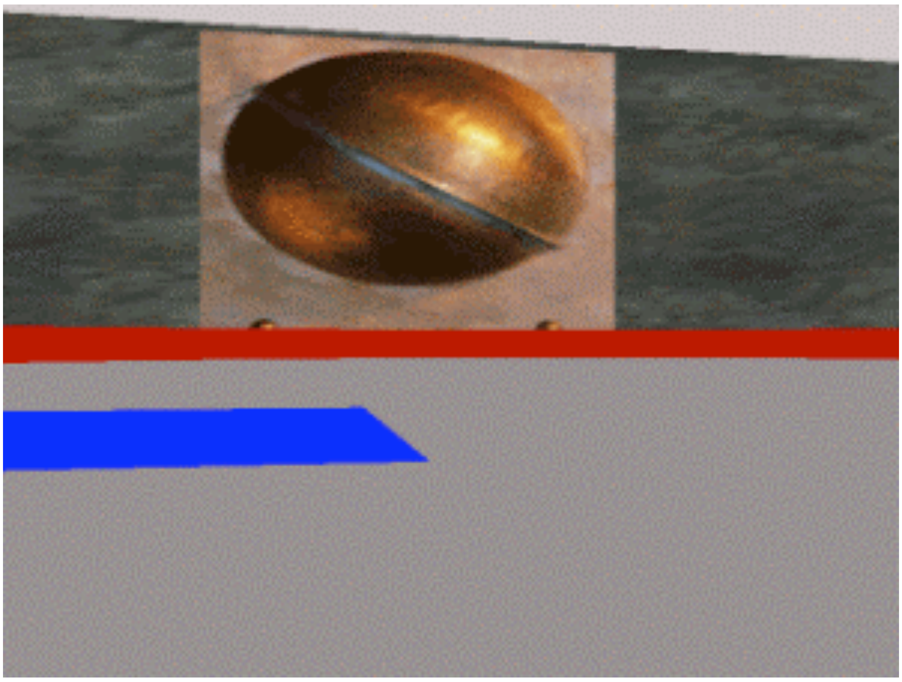


Figure 3. Desktop-based VE presented from a first person perspective employed by Kállai et al. (2007).

The perception of 'being in' a VE is called *presence* (for a review of this concept, see Ijsselsteijn, 2004). Presence requires directing attention to a spatially defined immersive medium that is sensitive to real-time feedback. Although the number and complexity of new technological solutions for VE is dynamically increasing, their real value in increasing presence and task performance is not always clear. Three-dimensional immersive VE, for example, are considered more ecologically valid test environments for complex navigation because they provide full body-based information that allows fast spatial updating (Ruddle & Lessels, 2006a). In contrast, complex navigation on a desktop-based VE interface can overload the cognitive capacities of the user and could result in reduced route planning and way-finding performances (Ruddle & Jones, 2001). This suggests that navigators on a 2D plane are occupied with details, such as movement control and perspective-taking, whereas these features are automated in a 3D immersive VE. Although advanced computer graphics might enhance the sense of presence and immersion for desktop VE, recent results suggest that real-time movement control and full body-based information are weighted more heavily than high visual fidelity (Ruddle & Lessels, 2006a).

When body-based information is not present, like in the case of most desktop VE, a good level of performance can still be achieved by keeping the task complexity to a minimum. This is to reduce the cognitive demands of the user by maintaining a simple VE control interface (Morganti, Carassa, & Geminiani, 2007; Riecke, van Veen, & Bülthoff, 2002). In fact, there is no conclusive evidence that participants in 3D immersive environments would actually acquire better quality spatial knowledge than in low-complexity desktop VE (Ruddle & Péruch, 2004). Immersive virtual technologies (e.g., helmet-mounted displays, HMD) can only improve some aspects of spatial knowledge acquisition, but they are not affecting others. For example, participants with HMD looked around more frequently and spent less time stationary while choosing a direction than in a 2D desktop setting; however, they travelled the same distances in both VE (Ruddle, Payne, & Jones, 1999). In summary, it is not fully understood which type of VE provides better spatial navigation and learning results. Further research is needed to determine what is the interaction between environmental constraints of a VE and spatial performance. Chapter 3 of this thesis will address this question in more details using a high fidelity, 2D desktop VE.

Ruddle and Lessels (2006b) suggested three hierarchical levels of metrics to evaluate spatial wayfinding in any VE task performance analysis, behaviour analysis and cognitive rationale analysis. The level of task performances refers to direct measures on how well the user executed the task. These include completion times, distances travelled or errors to navigate from the start to finish (Durlach et al., 2000). The second level is about behavioural search trajectories affecting spatial knowledge acquisition (Kállai, Makány, Karádi, & Jacobs, 2005; Ruddle & Péruch, 2004; Tellevik, 1992; Thinus-Blanc & Gaunet, 1997). It is particularly interesting to look at how a physically effortless virtual space could affect spatial learning and this question will be directly addressed in Chapter 4 of this thesis. The last level of investigation in a VE is concerned of higher-level cognitive strategies, such as processes of decision-making or cognitive styles. Methods of measuring these in a VE may include qualitative techniques, such as think aloud (e.g., Gamberini, Cottone, Spagnolli, Varotto, & Mantovani, 2003), interviews or questionnaires (e.g., Lawton, 1996; Sas, 2004).

Computational Model Space

In both natural and social sciences, computational models and simulations play an increasingly significant role as an investigative-experimental technique and as a hypothesis generating and testing tool (Hartmann, 1996). ‘Model’ and ‘simulation’ are often used as synonyms despite that, according to Hartmann, a model is a generic set of static assumptions about some system, whereas a simulation is a special dynamic model that imitates one process by another process. For the purpose of the present discussion, I will focus on computational models – mostly Agent-Based Models (ABM) – that could operate either statically or dynamically depending on the underlying rules of their basic unit: the artificial agent.

ABM are advantageous in their capacity to understand individual actions and behaviours as well as self-organizing social phenomena (Epstein & Axtell, 1996). Goldstone and Janssen (2005) argue that a great relevance of this approach to cognitive science is how it considers cognition as a result of “interactions among people and their environments” (p. 424). In the spatial context, Makány, Makowsky, Meier, and Tavares (2006) presented an example for such interaction in an ABM with the simulation of crisis-driven ethnic migration. In this dynamic social model, simultaneously migrating artificial agents assigned to their social-ethnic networks were monitoring their spatial environments for any threat to their personal security (Figure 4).

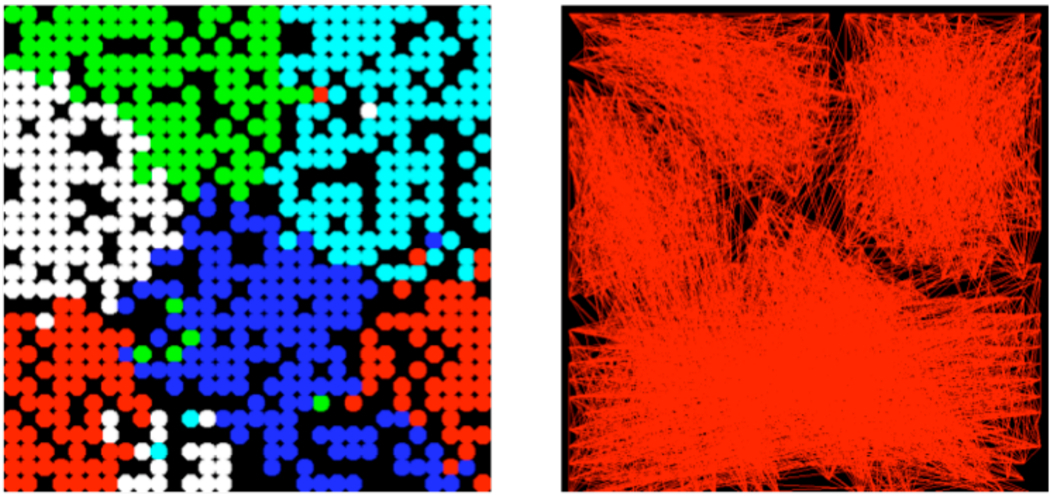


Figure 4. ABM of crisis-driven ethnic migration used in Makány, Makowsky, et al. (2006). Coloured dots on the left represent different ethnicities and their social connections are visualized on the right.

Each agent had constantly evaluated the expected utility of staying within an ethnically similar neighbourhood contrasted to a locally perceived general risk factor. The two-dimensional modelling space where these agents existed was also topographically weighted, so that the central areas of this 'virtual world' represented a higher incentive for the individuals than the peripheries. The results of this modelling study showed that (a) ethnic regionalization and migratory patterns depended on the relative size of the perceived risk; and (b) that spatial proximity of different ethnicities might lend greater stability to the entire network than more homogeneous ethnic landscapes. This is relevant to the present discussion because it demonstrates the strength of ABM as a spatial cognition research tool and more specifically that the geo-social environment can have a significant role in influencing individual spatial decisions.

Further examples of exploring multi-agent modelling spaces include the earlier mentioned space syntax approach (Hillier, 1996). Simulated urban spaces provide accurate yet inexpensive research grounds for understanding collective human spatial behaviour in an otherwise uncontrollable complex metropolitan environment. The focus of investigation in these studies is the identification of the cognitive and behavioural aspects of the individual agents (Agarwal & Abrahart, 2003; Benenson, 1998). Notice the similarity between previously discussed evaluation methods with physical or other abstract spaces. This also indicates that the basic rules underlying spatio-temporal dynamics are the same both in physical and in computer simulated spaces.

Although ABM are more commonly used to study complex, multi-agent social situations, it is not exceptional to simulate the spatial behaviour of intelligent single agents (Russell & Norvig, 2003). This can also be seen in the definition of single agents: "a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future" (Franklin & Graesser, 1996, p. 4). In times when there is no neighbour present in the computational space, the autonomous agent still performs its task according to the operating rules. This is analogous to physical spaces, where the individual can explore and interact in isolation from other individuals. Such cases provide unique opportunities to investigate the individual spatial cognitive and behavioural processes. Chapter 5 will present a study with such an ABM, where individual agents are exploring their environment by simulating the spatial heuristics observed in humans.

Information Space

Finally, I characterise information spaces from a spatial cognition perspective. Information space is an abstract space that encompasses a set of distributed online resources. The web is considered the archetypical task environment for information space (Benyon, 2005). It is a complex system of online information that is not limited to the Internet. The latter is a network of physically linked computers, whereas the former represents hyperlinked information that can be on a local machine, a secure intranet e-learning site or publicly available Internet domains.

A spatial metaphor is used as a conceptual framework to characterise information spaces (Boechler, 2001). Similar to physical environments, online abstract spaces are both semantically and spatially organised, so that a structure of the online content can be obtained based on both the meaning and the relative location of the pieces of information. These structures can be represented and measured using graph theory notations (Newman, 2003). Vertices (or nodes) are the pages visited and edges are the links followed (Figure 5).

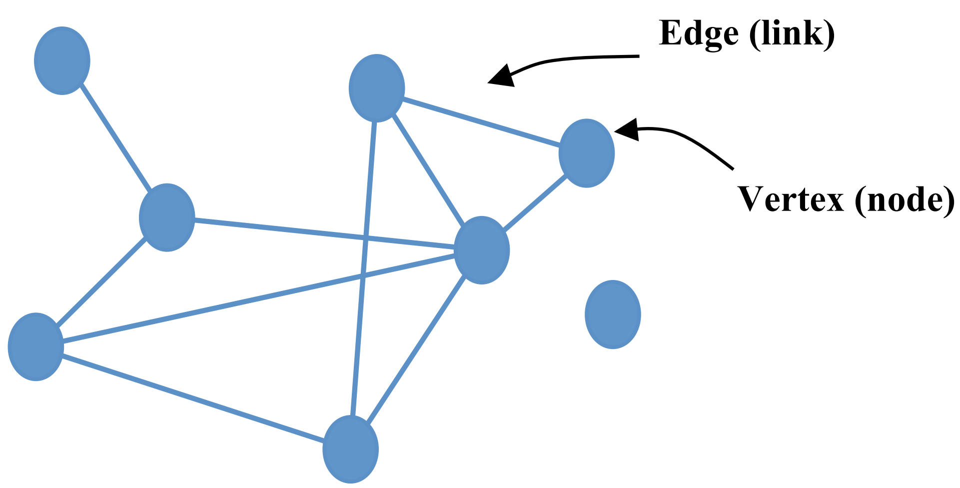


Figure 5. Graph theory notations of an information space (adapted from Newman, 2003). A vertex or node can represent a website or any information location. An edge or link is the connection between two vertices.

The degree of a graph indicates the number of edges connected to a vertex. For example, Google uses a method called PageRank to assess websites on the Internet, which considers the degree of each site relative to another ones (centrality). The most important site with the highest PageRank value comes up first in Google's search results list. In other words, the power of an information space search is not the specificity of the content, but the 'linkedness' of the page (Newman, 2006; Newman, Barabási, & Watts, 2006). These (and other) graph theory measures in spatial cognitive are collectively called *visitation patterns*.

People developed adaptive visitation patterns to acquire and use desired knowledge within an information space to improve decision-making and problem-solving success (Pirolli, 2005; Pirolli & Card, 1999). There are two characteristic navigation problems in an information space: (a) choosing which link to follow and (b) deciding when to visit another node (i.e., website). Information foraging theory addresses such human-information interactions and I will discuss this in more details in relation to the concept of optimality in the next section. In addition, the last empirical chapter of this thesis will present a study of navigation strategies within differently designed e-learning webpages.

Section Summary

In this section, I characterised those spatial environments that will be used for empirical analyses in the following chapters. At first, the dynamic interactions between the navigator and its environment were discussed using the example of self-organising trails. The issue of individual versus collective spatial behaviour was presented and I concluded that both approach are targeting, though on different levels, the same underlying question about how navigators allocate their spatial resources. Consequently, I analysed the characteristics of physical and abstract spaces and found that the same cognitive and behavioural mechanisms are involved when people interact with them. In the next section, the review focus will be on the theoretical issues of optimality, efficiency and performance in spatial cognition.

Optimality in Spatial Cognition[1]

In this section, the question of optimality ("rationality" in the economics literature) in spatial cognition will be discussed. Evaluation of a behavioural action is difficult, as multiple criteria could exist for how to solve a task optimally (Ruddle & Lessels, 2006a). For example, someone living in Milan could fly to Rome relatively quickly on an aeroplane; however, that person would miss the beautiful landscapes of North Italy that the same trip with a car would entail. Travelling time and visual aesthetic, in this case, are the two factors that need to be evaluated by the navigator. This section will describe how behavioural economics and various foraging theories address such issues of optimal spatial cognition. Finally, I will integrate the ideas from these fields and propose two measures (cognitive and behavioural) of spatial efficiency.

Behavioural Economics

Behavioural economics, at the borders of psychology and neo-classic economic theory, is the scientific examination of human cognitive mechanisms involved in economic decisions (Camerer, Loewenstein, & Rabin, 2003). Studies in this field, in contrast to standard normative models in economy, take the assumption that humans do not always act as rational agents and consequently their behaviour patterns are biased (Kahneman, 2003).

Human rationality is bounded (Simon, 1955, 1979). This means that human cognition and decision-making involves extraneous elements that cannot be solely predicted and fully interpreted by analytical decisions based on the available information. One of the reasons for this is the limited resources of the cognitive system itself. The computational and storage capacity of human memory is restricted, and in order to act efficiently, simplified solutions (known as heuristics) need to be applied.

People do not carry out exhaustive searches on the contents of their memory when dealing with everyday situations. Tversky and Kahneman (1974) demonstrated that people utilise heuristic shortcuts in their decisions, creating probability judgements, which could deviate from statistical (rational) principles. For example,

[1] Part of this section was published as Makány, T. (2006). Optimality and cognition: Shortest paths and smartest brains. *Periodicals of Implicit Cognition, 4,* 1-6.

when people are asked whether it is more likely to come across English words that begin with an ‘r’ or where ‘r’ is the third letter, the first option is chosen more often. This incorrect answer is based on a heuristic bias that people can more easily recall words from their memory that begin with an ‘r’ than those, which contain ‘r’ as the third letter.

Bounded rationality is, nevertheless, very rational. One could argue in favour of such descriptive theories as behavioural economics that adaptive cognition acknowledges its own boundaries and acts accordantly (Mérő & Mészáros, 1990). When humans do the best they can (and not the best possible), economists describe that behaviour ‘rational’ and ecologists use the label ‘optimal’ (Lea, 2006). This common understanding for a non-maximising rationality is the major contribution of behavioural economics to the study of cognitive processes.

As demonstrated by Simon (1979), people are generally highly selective about their information acquisition and utilization. Only a fraction of overall information is processed, which makes the available cognitive resources scarce. In addition to the previously mentioned internal capacity limitation of the cognitive system, this is the other reason – an external limitation – that leads to a bounded rationality. The core claim is that there are relative costs associated with selecting the relevant information such as the cost of processing an item of information, and the cost of acquiring information (Payne & Bettman, 2004). A trade-off is presented between deliberation (processing information), which could represent a high cognitive or emotional cost; and elaboration (acquiring information), which is a procedural activity (Conlisk, 1996). Both sides of the trade-off could manifest in an increased use of heuristics. For example, when writing a literature review in the library, the action of looking up an interesting reference involves the student both reading the book (cognitive cost of processing) and picking it up from the shelf (active energy cost of acquisition). The costs and benefits of acquiring and processing the information in the book determines the behaviour of the student (i.e., get the book immediately or only after reading other materials) or whether or not the item is processed at all (i.e., find sources that are more easily accessible). In the next section, I will focus on formalised theories of spatial resource utilization that are based on the assumption of bounded rationality.

Optimal Foraging Theory

Optimal Foraging Theory (OFT) is a theoretical and empirical construct of evolutionary ecology that focuses on the optimality of searching behaviour of cognitive systems (MacArthur & Pianka, 1966). OFT offers tools to analyse the utilization of food, mating and space resources and predator-prey interactions. As a result of natural selection, both human and non-human species are evolved to make use of ‘patchy’ spatial environments (i.e., with not equally distributed resources) by optimising their spatial search strategies and diets. OFT assumes that, on an aggregate level, animals living within a certain environment have achieved a steady-state equilibrium in terms of their group foraging efficiencies, and no further improvement is possible (Bell, 1991).

Behaviour on the level of equilibrium is descriptively rational (Lea, 2006). Specifically, optimal foraging routes can be approximated based on the spatial distributions of distinguishable patches with either reward (food or mating partner) present on them or not. The probability distributions in optimal animal foraging do not follow Gaussian or other classical shapes, but they rather show scale-free power-law properties (Viswanathan et al., 1999). When the lengths of individual trips show this power-law distribution, the foraging pattern is called a Levy-flight or random walk pattern. Despite its name, a random walk is not totally random. In fact, it is relatively cost efficient as it includes a number of small trips in the immediate surroundings randomly alternating with a few phases of fast ballistic motion. Such intermittent behaviour of Levy-flights is the best search strategy to minimize the probability to return to the same site again (a disadvantage of random search) together with the maximization of the number of newly visited sites. This makes Levy-flight distributions the most efficient motion patterns for the individual forager (Bénichou, Coppey, Moreau, Suet, & Voituriez, 2005). A further justification for the optimality of such exploration strategy is how commonly this strategy is applied in nature. Experimental results confirmed that Levy-flight distributions provide accurate predictions for actual observed foraging behaviours in a large variety of animal species (Bénichou et al., 2005; O'Brien, Browman, & Evans, 1990; Viswanathan et al., 1996). However, recent evidence points out that humans might be an exception from this power-law rule, as our everyday travel patterns show other types of regularities that culminate in spatial distributions different than random walks (González et al., 2008).

One possible reason for this could be the more intensive utilization of the available cognitive resources, such as memory and mental manipulations, in our spatial searches. This explanation in itself, however, is not satisfactory, especially when compared to species such as the grey squirrel, which produces and remembers a large number (over 3000 nuts-per-year) of unmarked and scattered hoards of food over a large territory (Macdonald, 1997). Nevertheless, optimal foraging requires the aligned processing of memory and navigation behaviour. Empirical evidence with humans illustrated that extensive demand in optimising navigation enhances relevant cognitive functioning and alters corresponding brain structures. For example, in a neuroimaging study with London taxi drivers, significant differences in the structure of the right posterior hippocampus were reported in these highly trained expert navigators compared to non-expert controls (Maguire, Frackowiak, & Frith, 1997). Nevertheless, structural brain differences are highly task specific (e.g., spatial domain, Maguire et al., 1997; in the musical domain, Schlaug, Jancke, Huang, & Steinmetz, 1995) and not always found in more general memory tasks (Maguire, Valentine, Wilding, & Kapur, 2003).

As the above studies demonstrate, OFT offers a great theoretical and practical tool to analyse spatial strategies of foraging animals in a patchy environment. It is based on the assumption that state of equilibrium can only be achieved through a descriptively optimal behaviour (Lea, 2006). However, as the cognitive complexity of a foraging decision increases – as is the case with the taxi drivers in Maguire et al. (1997) study – the planning and mental mapping mechanisms of spatial cognition contribute more and more to the optimality of behaviour. As it is demonstrated in the next section, in spaces where the physical constraints of the environment are reduced (i.e., in abstract spaces) this cognitive aspect is even more dominant.

Information Foraging Theory

In the spirit of evolutionary ecology, Pirolli and Card (1999) proposed in their Information Foraging Theory (IFT) that goal-oriented adaptive cognitive systems optimize their information acquisition and decision-making strategies in the information space – both digital and analogue - to maximize valuable knowledge gained. Based on the rational analysis approach (Anderson, 1991), the task environment of information spaces includes costs of accessing, recognising and handling information, which the adaptive information forager ('user' in this context) attempts to minimize. As discussed in the case of physical environments, these task costs are similarly not intrinsic properties of the informational resources (e.g., documents, webpages) but dynamically changing according to the interaction between the individual and its environment (Pirolli & Card, 1999; Schiller & Cairns, 2008).

In the IFT literature, navigation through information spaces involves evaluating the perceived value, cost or access paths to information sources represented as spatial cues such as hyperlinks, icons or catalogues, often called as information scents (Pirolli, 2003). The most preferred means of information scenting on the web are hyperlinks (Katz & Byrne, 2003). These spatial cues are text or graphical representations of navigable target destinations located distantly in the information space. There is a growing consensus that the psychological mechanisms underlying information scent-following are the same as in spatial searches in other (both physical and abstract) environments (Benyon, 2006; Hills et al., 2008; Pirolli, 2005).

Models of IFT aim to describe the factors determining scent-following and predict user behaviour within the particular task environments. An example of this is the quantification of the uncertainty of the web user about the correspondence between a hyperlink (scent) and the linked information resource (unexplored webpage), as each navigational choice represents a potential risk of suboptimal resource utilization (Pirolli, 2005). Predicting decisions under uncertainty also falls under the research realm of the previously mentioned behavioural economics (e.g., Tversky & Kahneman, 1974).

Another widely investigated question related to IFT is the spatial arrangement of scents between and within information environments in order to achieve optimal (or desired) user behaviour (Card et al., 2001; Makány, Engelbrecht et al., 2007). Although the web is a lattice, the idealised visitation paths are represented over generalised graph structures (e.g., linear, tree, star, etc.). Finding the appropriate graph structure of information scents to present to the user is equally a theoretical and practical challenge. The final empirical chapter of this thesis investigates this question within an applied context of e-learning websites with different levels of structural complexities.

Efficiency and Performance

The allocation and utilization of cognitive and behavioural resources has evolved as a consequence of natural selection (Bereczkei, 2000; Cosmides & Tooby, 1987). These are adaptive mechanisms that increase the chances of survival in competition with other members of the species or other species. A great deal of behavioural richness can be observed within adaptive agents (i.e., genes, memes, human societies, etc.) interacting with their environments. In fact, the diversity in nature is an adaptive answer to the continuously changing demands of self-sustainability. Dawkins (1976) noted that evolution has three potentials to increase the expected fitness of any species: (1) to increase action efficiency (e.g., run faster than the other); (2) to increase sensation efficiency (e.g., see further); or (3) to introduce more complex decision-making strategies (e.g., rely more on cognitive resources). Consequently, there is a strong selection pressure to improve any of these three potentials in a way that is not yet exceeded by others. However, there is a trend that the more complex the organism (i.e., humans) the more likely that the third option will be applied by developing intelligent programs to exploit natural resources.

As discussed earlier, bounded rationality suggests that humans with limited information processing capabilities and scarce resources are not always able to exploit their environment fully (Simon, 1955, 1979). Rather, they apply heuristics that help them to achieve a ‘good enough’ level of performance, with balanced cognitive and behavioural efforts. Simon’s concept of ‘satisficing’ behaviour (choosing among a subset of behaviours when information processing is limited) postulates two levels of optimality: global and local optima. With reference to cognition, the former represents perfect knowledge acquisition and utilization, whereas the latter permits trade-offs between certain cognitive abilities within the adaptive range.

Adaptive human cognition is aiming for local optima. To explore this, Anderson (1990) compared his participants’ cognitive performance to a global optimum criterion principle. The results of various tasks on memory, categorization, causal inference, and problem solving were all slightly below the level of this criterion. This suggests that our cognitive system allocates its limited resources selectively according to a satisficing rule in order to adapt efficiently to the available environmental situation.

Studies of cognitive evolution emphasise that our species spent most of its evolutionary history as hunter-gatherers (e.g., Wynn, 2002). The specific environmental challenges that governed the development of cognitive mechanisms were, therefore, spatially determined. Numerous hunting and storage sites, rival tribes, and geographical obstacles had to be remembered over relatively huge distances, and regular chases for food presented complex spatial optimization tasks to our ancestors.

The evolution of spatial strategies favoured those hunter-gatherers who could most efficiently optimize their explorations both in terms of the cognitive costs of remembering routes and the behavioural energy costs of travelling (Byrne, 1995; Menzel, 1973). In novel environments where inferential relations had to be represented, a flexible spatial strategy enhanced navigation and wayfinding. In such cases, significant cognitive effort had to be spent on computing novel routes, or alternatively choosing a different learnt path. However, if the task involved the use of only familiar spaces, a more rigid and routine series of spatial actions (i.e., following well-learnt routes) led to efficient performance (Hartley et al., 2003). In these cases, any extra cognitive load would have interfered with navigation.

Not surprisingly, laboratory studies found that animals apply this double-sided strategy not only by optimizing their energy consumptions during spatial explorations but also by economizing the cognitive costs of remembering the spatial layout (Cramer & Gallistel, 1997). Chimpanzees (Menzel, 1973), other primates (de Lillo, Aversano, Tuci, & Visalberghi, 1998; Di Bitetti, 2001; Di Fiore & Suarez, 2007), and cats (Page & Dumas, 2003) were reported to show a trade-off in their search strategies reflecting the distance they wish to travel or the cognitive investments associated with learning routes between sites of interest. The final section of the introduction will expand the details of these studies and emphasise the need for further empirical research in how humans perform similar trade-offs in their spatial optimization.

Section Summary

In summary, this section was focusing on the questions related to optimality in spatial cognition. Examples from Behavioural Economics, Optimal Foraging Theory and Information Foraging Theory were presented to show theoretical and practical approaches that provide models of how optimality within different task environments can be achieved. The bounded rationality of the human mind operates with 'heuristics strategies' in order to adaptively respond to situations with information overload. Our cognition does the best it can, but certainly not always the best that is possible. Both economics and ecology assume that trade-offs are essential mechanisms in optimization. In the spatial domain, the two sides of this optimization are cognitive computational costs and travelling behavioural costs.

Spatial Strategies

In this section I review the different spatial strategies of navigation. Spatial strategies can be defined as the mental representations of one's own position in relation to the surrounding spatial environment, including a goal position and an intentional plan to reach that goal via an optimal route (Levitt & Lawton, 1990). This is, however, only the *cognitive* part of the definition, while the *behavioural* part is concerned about efficiency of both the execution and the control over these knowledge representations. Therefore, a full definition of spatial strategies also needs to reflect on the observable patterns of spatial travel that records how well the intentional plan is translated into action. These two aspects of spatial strategies (cognitive optimization and behavioural efficiency) together reflect the dual tasks involved in spatial cognition often labelled as route-planning and distance-travelling, respectively (Chen & Stanney, 1999; Freundschuh, 2004). Consequently, *spatial strategies are defined here as those heuristics that allocate available cognitive and behavioural resources for solving spatial navigation tasks.*

The first problem with spatial strategies is how to infer a goal or purpose from the observable patterns of movement. For foraging animals in the wild, Janson and Byrne (2007) labelled this theoretical and practical difficulty as a "proverbial *black box* problem" (p. 357). However, the same problem applies to humans as well. Language acquisition and spatial reasoning skills arguably place humans in a unique position as they enable us to develop more unified representations than non-verbal animals (Shusterman & Spelke, 2005). And as most spatial strategies are intuitive, pre-verbal and heuristic in their nature, it is likely that even humans have a relatively low level of conscious access to these representations. Therefore, spatial strategy analysis is applicable for the spatial representations of all cognitive animals with sufficiently flexible and sophisticated mental and behavioural abilities to intently deal with their environments (Byrne & Bates, 2006).

At the core of spatial strategy analysis is the basic assumption that animals – including humans – navigate optimally in their environments by remembering the locations of their spatial resources (e.g., Gallistel, 1990; Menzel, 1973; Shettleworth, 1998). This brings us back to issues of optimality discussed previously. How optimal is a spatial strategy? What is the most optimal strategy for navigation? The answer is that when spatial strategies result in a near-optimal behaviour, they are considered as (locally) optimal allocations of the available resources (Charter & Oaksford, 1999). Therefore, there is no 'always winner' (global optimum) spatial strategy and their level of efficiency represents a compromise between individual abilities and environmental resources.

Previous studies are reviewed below in two steps to further understand the interaction between cognitive optimization and behavioural efficiency. First, studies about cognitive load are discussed. Second, the focus will be on a group of studies describing different behavioural patterns.

In the review of how mental representations are organised during spatial foraging, the emphasis is on the goals behind the observed behaviour. Such spatial goal analysis seeks to explain the reasons of spatial cognition by describing individual (or group) differences in terms of higher level cognitive or biologically determined issues. At the centre of this approach is the concept of a meta-level spatial representation -- a cognitive map that processes top-down spatial information. However, the optimal utilization of this cognitive map is constrained, not only by the limited resources of the external environment, but also by the limitations of cognition itself, including memory load (Di Fiore & Suarez, 2007), familiarity with the space (Siegel & White, 1975), expertise (Maguire, Spiers, et al., 2003), cognitive style (Gazit & Chen, 2003), or more biologically determined issues such as sexual dimorphism (Jones, Braithwaite, & Healy, 2003; Lawton, 1994), evolutionary processes (Haun, Call, Janzen, & Levinson, 2006; Hills, 2006), age (Moffat, Kennedy, Rodrigue, & Raz, 2007) or anxiety levels (Kállai, Kerekes, Osváth, Makány, & Járai, 2002; Lawton, 1994).

Conversely, studies on the behavioural efficiency of spatial behaviour represent a bottom-up approach aimed at describing the observable travel routes and quantifying the efficiency level during the actual performance. In the focus of these studies are the observable and repetitive features of spatial strategies that could be typical segments of a trajectory (Hamilton, Rosenfelt, & Whishaw, 2004; Kállai et al., 2005), object visitation sequences (Cramer & Gallistel, 1997; Gaunet & Thinus-Blanc, 1996; Lessels & Ruddle, 2005), or frequently re-occurring exploratory patterns (Gamberini et al., 2003; Graziano, Petrosini, & Bartoletti, 2003; Makány, Redhead, et al., 2007; Sas, O'Hare, & Reilly, 2005). These studies are either measuring a priori defined behaviour categories (e.g., thigmotaxis, Kállai et al., 2005) or applying classification algorithms that can identify these features (e.g., cluster analysis, Makány, Redhead, et al., 2007; Sas et al., 2005).

Cognitive Optimization

The notion that cognitive animals represent their environments and the available resources within a spatially organised mental structure gives way to different interpretations with regards to what is the goal of these knowledge representations and how optimally is this being utilized (see also previous sections on Spatial Learning and Optimality).

Di Fiore and Suarez (2007) suggested that primates use habitual routes to reduce the cognitive load of their spatial resource allocations. This small number of well-known routes provides a less demanding task environment for their spatial search. In another study, capuchin monkeys also tended to avoid revisiting areas that were used recently to maximize their foraging potentials (Di Bitetti, 2001).

The evidence for a cognitive strategy that optimizes memory load has been most convincingly reported in people with visual impairments (Gaunet & Thinus-Blanc, 1996; Hill et al., 1993). Gaunet and Thinus-Blanc (1996) compared early-blind and blindfolded control participants in spatial exploration tasks. A baseline measure of activity and object visitation sequence pattern was taken on the first encounter of the room, and compared to the performance in subsequent trials, which contained several rearrangements of the object locations of the room. The results showed that although early-blind people were very good within their familiar environments, they had an impaired reaction to changed layouts compared to blindfolded controls. The authors argued that early-blind people used more sequential encoding strategy of the space to reduce their overall cognitive loads; however, that strategy only associated the relative position of one object to another, rather than obtaining a global (map-like) representation of the space. This non-optimal strategy involved “successive visits to the four different places [landmarks] frequently ended with a return to the one first visited” (p. 972). Hence, they had to repeatedly rebuild their route representations every time a change had occurred.

Lawton (1994, 1996) also found differences in the cognitive optimization of spatial strategies based on the acquired levels of spatial representations. When his participants navigated using a ‘route strategy’, they employed sequential information processing as they slavishly followed the same specific routes that once led to the destination. Conversely during an ‘orientation strategy’, relative positioning and continuous self-monitoring with respect to specific landmarks were used, such as compass directions in outdoor environments, or building configuration in indoor environments. Although route and orientation strategies could be equally efficient in most wayfinding tasks, orientation strategy offers more flexibility in a relatively unfamiliar environment.

These studies point out that there is a relationship between the level of task complexity and the optimization of the spatial strategies. In complex navigation tasks, where inferential relations have to be represented (i.e., the cinema is downtown, a few blocks away from the central library), a flexible exploration strategy could enhance wayfinding accuracy and efficiency (Hartley et al., 2003). In such cases, reasonable cognitive effort has to be made to compute a novel route or select a previously learnt path. However, if the task is easy enough to be solved by the use of only simple action-based representations, a more rigid and routine series of spatial actions (i.e., following a few well-learnt paths) could lead to a better performance. In such cases, any extra cognitive load would rather disturb the execution of well-learnt route following. In simple tasks, a sequential solution could provide the best strategy with the most efficient paths. However, relying only on a single route for more complex navigation tasks could reduce the chance of finding the most optimal way.

Wayfinding strategies are also dependent on developmental and personality factors, such as childhood navigation experiences and adulthood fears. For example, Kállai and his colleagues (2002) found strong correlations between spatial strategy, anxiety and childhood attachment factors. Participants with high anxiety scores were less likely to apply an orientation strategy and used mostly a landmark based route strategy. The authors argued that spatial anxiety develops as a consequence of an overprotective parental behaviour that significantly increases all safety-seeking strategies in adulthood. In spatial learning terms, these behaviours facilitates route following, even in situations where an orientation strategy would be more advantageous.

Extensive research has reported gender differences in spatially involved tasks and wayfinding strategies (e.g., Kimura, 1999; Parsons et al., 2004). Most of these studies showed male advantage in spatial abilities and navigation performances. A detailed investigation into the gender differences of visuo-spatial working memory, however, pointed out that males are only better in mental image maintenance and manipulation, whereas females have more rapid access and retrieval capabilities (Loring-Meier & Halpern, 1999). Furthermore, other factors such as task dependency (Sandstrom, Kaufman, & Huettel, 1998), different neural activation (Gron, Wunderlich, Spitzer, Tomczak, & Riepe, 2000) and hormonal fluctuations (McCourt, Mark, Radonovich, Willison, & Freeman, 1997) make the gender argument more sophisticated. The conclusion from these studies is that both biological development and the surrounding environment have an effect on gender differences of spatial strategies. As a good example, evolutionary psychologists have proposed several hypotheses to explain the relationship between spatial strategies and gender differences (for a summary, see Jones et al., 2003). The main argument within these theories is that males have better spatial abilities because they had to navigate longer distances for hunting and for mating purposes and consequently, they had to remember larger spatial arrays of locations. This evolutionary pressure favoured more flexible orientation strategies in males. In contrast, as females generally were not involved in hunting and as they were more vulnerable during reproductive periods, they stayed within close vicinity to the households (i.e., local food resources). Instead, females adopted landmark spatial strategies as these fitted better with their reduced mobility. Although these evolutionary hypotheses are highly plausible, their experimental predictions need further testing in order to support them persuasively (Jones et al., 2003).

Finally, within the discussion of cognitive optimization, the question of cognitive styles warrants mention. Cognitive style is an overall set of preferences that an individual uses to process information (Ford, 2000; Sas, 2004). Within the spatial domain, this is more than an individual navigation strategy (e.g., route following), which refers only to the choices in a particular spatial situation. Cognitive style of spatial cognition reflects the aggregate pattern of personality attributes and cognitive decisions made by the individual within his or her environment. For example, Gazit and Chen (2003) investigated cognitive styles of high school children in a free exploration task of a virtual solar system. They found three exploratory patterns, and they named them after the typical movements of three animals: butterfly, bee and eagle. The butterfly pattern consisted of short visits to the virtual planets in a sequence, with little attention paid to smaller details. In contrast, the bee pattern observed the objects thoroughly with zooming. Finally, the eagle pattern flew around the planetary objects and explored the surrounding environment more comprehensively. The authors argued that the shift between the frames of references was an important contributor to the spatial knowledge acquisition and that the more perspective-taking patterns helped the children to navigate better in the virtual solar system.

A criticism of descriptive studies such as Gazit and Chen (2003) is that although they provide notable insights into spatial strategies most of them are either qualitative (i.e., cognitive styles) or hypothetical (i.e., evolutionary theories). To establish a stronger claim for the relevance of strategies (including cognitive styles) within spatial cognition, more experimental manipulations and simulation studies are needed (Janson & Byrne, 2007). With controlled changes in the environmental conditions (e.g., alternating available spatial information resources), or more objective performance measures (e.g., learning efficiencies) spatial strategies could be further improved and better validated. These experimental research aspects are more prevalent in the studies reviewed in the next section.

Behavioural Efficiency

Investigating the processes of cognitive optimization – for example cognitive load – is only partially sufficient to understand spatial strategies. As mentioned earlier, inferring strategic goals of resource allocation based on observations of foraging behaviour can be problematic (Janson & Byrne, 2007). It is essential to interpret spatial travel patterns, such as exploration styles, route choices or landmark use, as emergent properties of the underlying cost-benefit analyses of the cognitive system. Travelling, either in a physical or in a virtual space, has certain costs that could modify mentally planned routes. Therefore patterns of spatial movement almost always reflect a strategic compromise (or trade-off) to an optimal ratio between cognitive load and behavioural efficiency.

The analysis of exploration patterns (i.e., routes, paths, trajectories) represents an interesting and novel approach that describes spatial strategies and quantifies their levels of efficiency (Gaunet & Thinus-Blanc, 1996; González et al., 2008; Kállai et al., 2005; Lahav & Mioduser, 2004; Lessels & Ruddle, 2005; Ruddle & Lessels, 2006b; Sas et al., 2005). These studies investigated frequently travelled routes in novel environments and their related efficiencies in finding targets. These exploration patterns encapsulate a history of how the environment was discovered and remembered. For example, Kállai et al. (2005) found that often revisited regions or repeated object exploration sequences corresponded to more detailed sections of spatial representations, and these were also reliable indicators of subsequent navigation performances. Consequently, these patterns are the *behavioural fingerprints* of spatial strategies. In other words, the observable routes of travel, if analyzed properly, could provide valuable information on the process of spatial cognition as a whole.

A recent study with an impressive sample size of over 16 million registered spatial movements for 100,000 anonymous mobile-phone users showed that human mobility patterns can be described by a relatively few number of simple navigation rules or travel strategies (González et al., 2008). The mapping and detailed statistical characterisation of the individual trajectories revealed that one of the most common mobility patterns is to return frequently to a few significant locations. This is not surprising in itself, as most of us go home at the end of each day or visit our parents regularly. However, the method presented by Gonzáles et al. could provide a practical tool to statistically describe large and dynamically changing data of mobility patterns.

In other studies focusing on the dynamics of spatial learning, exploratory patterns were analyzed within their temporal context (Hamilton et al., 2004; Hills et al., 2008; Kállai et al., 2005). Shift points (i.e., specific points of learning, when one strategy changes to another) were found when one strategy was replaced by another strategy during the process of spatial learning. Hamilton and his colleagues (2004) found that the dynamic properties of the trajectories are different in the initial and in the terminal segments of the search pattern. Rats seem to utilise a more global spatial representation in their early search, determined by multiple distal features and landmarks of the environment. However, in the terminal stage of navigation, when the target location is anticipated, the swimming trajectory transforms into a direct, ballistic route, which is mainly influenced by a single cue. Hamilton et al. presented this shift point between the two segments that can be characterised by a radical change in the dynamic properties of the trajectories. Before that point, velocity showed sharp alternations. After the shift point, it monotonically increased until, immediately before the platform, it suddenly decreased as the animal arrived. More interestingly, there is a further characteristic of the navigation paths around this shift point. Initial headings have an angular deviation from a direct route to the platform and it is corrected only in the terminal stage. However, this final, ballistic segment is not auto-corrective; therefore, if the platform was missed by the rats, they did not persist in searching, but returned to the release location and attempted to execute the same route again.

There are further classification tools of exploratory patterns, which are based on matching the observed behaviour with the underlying goal (Graziano et al., 2003; Kállai et al., 2007; Kállai et al., 2005; Makány, Redhead, et al., 2007; Sas et al., 2005; Wolfer & Lipp, 2000). A typical example is ‘wall-following behaviour’, or thigmotaxis, that appears most frequently when the first encounter with a novel spatial environment is cognitively demanding and stressful (Creed & Miller, 1990; Jeanson et al., 2003). Exploratory trajectories during thigmotaxis follow the boundaries of the unfamiliar environment whereby participants learn about the global structure of the space. It also provides a frame of reference where a more detailed knowledge acquisition can take place. Kállai et al. (2007) found positive correlations between thigmotaxis in the early stages of spatial learning and general phobic avoidance scores. The authors presented evidence that emotive response happens in parallel to, and sometimes overrides, the cognitive elements of spatial learning. Despite some inconsistency in labelling, other studies found similar patterns in initial exploratory routes, named as ‘perimeter’ (Hill et al., 1993; Lahav & Mioduser, 2004; Lessels & Ruddle, 2005; Tellevik, 1992), ‘around-the-edge’ (Sas et al., 2005), or ‘close-the-wall’ (Sandstrom et al., 1998).

Another typical exploratory pattern is ‘circling’ (within a circular space) that is to move in line with the boundaries, yet not staying close to them (Kállai et al., 2005). The explorer monitors and follows the discovered configuration of the environment from distance while exploring other novel regions. Depending on the shape of the place whether it is a squared shape room these patterns can contain straight, axial lines or curved, arc trajectories in a circular mazes. Similarly to the previous pattern, different labels exist for this strategy including ‘grid’ (Hill et al., 1993; Tellevik, 1992), ‘circular’ (Sas et al., 2005), ‘circle and zigzag’ (Astur, Tropp, Sava, Constable, & Markus, 2004) or ‘lawnmower’ pattern (Lessels & Ruddle, 2005). Spatial exploration patterns, such as ‘thigmotaxis’ or ‘circling’, are predictive to the overall performance. Their presence or absence at various phases of spatial learning might indicate that the subsequent navigation is going to be optimal or suboptimal. This supports the view that observable and measurable exploration patterns are the *behavioural fingerprints* of spatial cognition.

Section Summary

This section provided a review of the existing literature of spatial strategies. Spatial strategies were defined as those cognitive and behavioural mechanisms that are related to the optimal allocation of the available resources in the surrounding environment. Two aspects of spatial strategies were presented in details: optimization of cognitive efforts and behavioural description of exploration patterns. Cognitive mechanisms are top-down and usually biologically determined influenced by factors such as gender, evolution, or cognitive style. Behavioural explanations focus on the simple bottom-up processes that can determine the target finding efficiency of navigation. Taking these two approaches together, an integrative study of spatial strategies enables us to analyse spatial behaviour and cognition systematically, both qualitatively and quantitatively, in terms of optimality.

In the next chapter, an experimental investigation of spatial strategies will be presented. The aim of the experiment is twofold. First, identify individual strategies within exploratory spatial behaviour and to analyse their efficiencies in navigation tasks. To accomplish this fully, and to capture the trade-off between cognitive load demands and travel energy costs, two measures of spatial performance will be introduced. The interaction between these measures has fundamental implications on understanding the mechanisms of spatial optimization. Second, present a novel method of exploration pattern analysis. This method is based on a cluster analysis algorithm that classifies strategic route patterns. Chapter 2 will serve as a baseline experiment for further investigations in this thesis.

Chapter 2: Spatial exploration patterns determine navigation efficiency in physical space

Strategies reflect both structural commonalities and programmatic patterns in cognitive and behavioural processes (Gordon, 2004). The value of a strategy reflects an optimized trade-off between the costs and benefits of the utilized behaviour. In the spatial domain, a strategy refers to a mental representation of the navigator's own position in relation to the surrounding spatial environment including a goal position and an intentional plan to reach that goal in an optimal way (Levitt & Lawton, 1990).

In previous studies of spatial cognition, task completion time was taken as a rough indicator of underlying spatial ability – such as learning (e.g., Morris, 1981) or mental manipulations (e.g., Shepard & Cooper, 1982). Decreasing escape times or path lengths in a water maze study, for example, would suggest that the animals are learning the spatial layout of the pool. However, it does not reveal much about the nature of learning; whether it was a qualitative or quantitative change (Thinus-Blanc & Gaunet, 1997). To analyse patterns of behaviour in spatial navigation further measures are required beyond the commonly applied method of task latency or travel distance.

Visible indices of navigation, like route choices or object visit sequences, are also measured with video recordings and independent observation tools with defined sets of coding guidelines (Graziano et al., 2003; Makány & Kállai, 2004). Alternatively, automated algorithms can identify behavioural patterns within large datasets of spatial information, such as video surveillance of pedestrian movements (Helbing et al., 1997; Sas et al., 2005). In fact, pattern formation of any complex spatial system can be described by the inherent syntax that determines their physical appearance (Hillier, 1996). Exploratory patterns are the behavioural manifestations of spatial strategies, and the frequency of recurrence is a quantitative indicator of how well that spatial knowledge is being utilized.

An earlier study of navigation behaviour found that global patterns change over time as a result of spatial learning (Tellevik, 1992). Three patterns were observed while blindfolded participants searched for target objects inside a room. Two of them (perimeter and gridline) were determined by the size and the shape of the environment. In the perimeter case, the participants limited exploration to the border of the environment, while the gridline referred to a strategy where participants walked straight from one side of the environment to the other. The third type of pattern was referred to as the reference-point strategy, where an object served as a point for each significant directional change. Tellevik argued that familiarity with the space allowed the participants to utilize object-to-object relationships rather than being preoccupied with the spatial characteristics of the environment (i.e. shape). Object based searching led to a better performance with a wider array of specific strategy patterns.

In a study by Kállai et al. (2005) recurring patterns of exploration behaviour were found to be good predictors of navigation performance and also as indicators for the temporal dynamics of spatial knowledge acquisition. Some patterns appeared more often during the early phases of spatial learning, such as the wall-following strategy, while others (e.g., visual scanning strategy) became more apparent when a reliable representation of the space had been formed. The authors concluded that human participants with poorer spatial abilities needed periodically to re-stabilize their positions in relation to the fixed perimeter; therefore, they used the wall-following strategy more extensively. In contrast advanced navigators could benefit from linking the allocentric external landmarks to each other, which allowed them to reduce their walking distances and to switch to a more memory dependent strategy.

Thinus-Blanc and Gaunet (1997) suggested that changes in exploratory patterns correspond to a multi-level acquisition and representation of spatial knowledge. A cyclic strategy enables a rough comprehension of the spatial relations. Back-and-forth movements refine the spatial knowledge allowing detailed and well-organised encoding. Consequently, the latter strategy leads to more efficient performance.

It should be noted however, that the reported optimal cyclic strategy in baboons (Gouteux, Vauclair, & Thinus-Blanc, 1999) was, in fact, found to be non-optimal in human data (Gaunet & Thinus-Blanc, 1996). This suggests that while animals utilize a more sequential exploratory strategy as their optimal foraging behaviour, humans achieve better scores if they are more concerned with constructing a detailed representation of the space. One interpretation of the discrepancy between the two sets of results could be that a compromising mechanism sets the balance between cognitive load and travelled distance costs. In a sense, humans utilize their cognitive abilities to take into account energy costs in spatial navigation tasks (Thinus-Blanc & Gaunet, 1997).

Despite the growing interest in recognising patterns of navigation, more empirical data are needed about how spatial knowledge acquisition and representation correspond to observable exploratory behaviour. A number of previous studies focused on the representation of spatial cues, such as landmarks or environmental geometry (e.g., Cheng & Newcombe, 2005), and on identifiable patterns during navigation (e.g., Thinus-Blanc & Gaunet, 1997). However, further investigations are needed to understand the relation between these two levels of spatial cognition.

Cognitive modelling of strategy representations offers a domain-independent analysis, which could be effectively utilised in any domain-specific system, such as the spatial domain (Gordon, 2004). A spatial strategy simultaneously reflects the structural pattern of navigational behaviour and the intentional act of a cognitive plan. These patterns are in the focus of the present study, as these are the observable and meaningful functional units of spatial cognition. The aim here is to connect spatial behavioural indices (e.g., travelled distances) with certain patterns of exploratory activity, and to provide plausible interpretations as to how strategies manifest on each structural level of spatial navigation.

In this chapter, initial exploratory patterns of human spatial navigation are analysed and related to navigation indices in a subsequent search task. An automated clustering algorithm is implemented to investigate emerging structural regularities within the routes of spatial exploration. The visual characteristics of these spatial patterns allow functional descriptions of the underlying exploratory strategy. The main question in this chapter is how people optimize their search strategies as observed through spatial patterns in a physical environment. Initial pattern groups are classified and compared to see if they determine performance in subsequent structured navigation. Additionally, to account for the difficulty to measure optimal performance unequivocally (see section on Optimality in Spatial Cognition), spatial navigation performance in this study is measured in two different ways: one examines the size of the search space to be remembered (Memory measure) and the other focuses on the total distance travelled (Distance measure).

Method

Participants

Forty-one undergraduate students from the University of Southampton participated in the study in exchange for course credits. Due to videotape error, two participants' data were erased, which left a total of 39 participants for the analysis (n = 39). They were 15 males and 24 females, who ranged in age from 18 to 50 years (mean age = 29.59; SD = 9.28). All participants gave informed written consent in accordance with the School of Psychology research ethics committee.

Apparatus

The experiment was conducted in a square room, 3.5 (length) x 3.5 (width) x 2.5 m (height). The walls were covered with black curtains that masked all external spatial cues outside the room. The room was evenly illuminated from the four corners by neon lights set in the ceiling. A speaker was hidden behind the curtains to communicate the tasks to the participants. A video camcorder was placed in the centre of the ceiling, to record the navigation activity from a bird's eye view perspective.

The room contained five visually identical open cardboard boxes placed in an irregular array on the floor. The dimensions of the boxes were 55 (length) x 55 (width) x 150 cm (height). Each box contained a similar-sized but visually distinct soft toy: a puffin, a yellow bird, a frog, a gorilla and a ball (Figure 6). Participants had to lean over the top of each box to explore its content. For a photographic illustration of the physical environment used in this experiment see Figure 2 earlier on page 37 of this thesis and see Figure 7 for a schematic view of the layout.

Figure 6. Soft toy objects used as landmarks inside the boxes: puffin, yellow bird, frog, gorilla and ball.

Procedure

The participants were led into the experimental room with their eyes closed. The start position throughout the experiment was a fixed location in the closest corner to the entrance door facing north. Initially to disorientate the participants, they were turned around their own body axes with their eyes closed before they started to explore. On a verbal signal from the experimenter who had returned to the adjacent control room, the participants opened their eyes and began exploring the space for one minute (*Phase 1*). They were asked to look into each of the five boxes and remember the objects inside and their locations within the room.

After this free exploration, all participants were instructed to visit first single objects than a sequence of 2-objects and finally 3-objects in fixed orders. They were allowed to choose any optional route and there was no time constraint (*Phase 2*). There were five single object trials, three 2-objects trials and three 3-objects trials. The order of object visits for single objects was: P (puffin); Y (yellow bird); F (frog); G (gorilla); B (ball); for 2-objects: F-Y; G-P; B-F; and for 3-objects Y-G-F; F-P-B; P-Y-G (3-objects). This task ensured that all participants were familiar with the layout of the physical space and the locations of each object.

In the final part (*Phase 3*), participants were asked to perform three consecutive 3-objects navigation tasks in any optional sequence they wished and in the most efficient way possible. The order of the three 3-objects tasks was: F-G-Y; B-P-F; G-Y-P. After the last task was completed, the experimenter entered the room and the experiment ended.

Results

Exploration Patterns

Two research assistants independently transcribed the video recordings of participants into spatial location coordinates. The consistency measured between the two researchers was over 95%. The transcription involved overlaying a matrix of 6x6 square grid on the image of the physical space and recording how frequently the participants entered each individual square. The size of each square was the size of one square box containing the target objects. For standardizing the matrices, the within variables - that corresponded to an individual square – were divided by their range. This equation of the scaling measure kept the differences in the variances intact that is highly influential for any further classification analysis (Milligan, 1996).

A cluster analysis and validation algorithm was applied to the exploration matrices (from Phase 1) to identify similar patterns within the dataset. A good clustering solution is deemed to have small within-cluster distances, and large between-cluster distances (Everitt, Landau, & Leese, 2001). At first, a hierarchical clustering with squared Euclidian distance metric and Ward's method was used to determine an estimate of the cluster groups. This suggested two main cluster groups within the data matrix (see dendrogram on Appendix A).

As hierarchical clustering represents mutually exclusive categories in a nested structure, a further step was needed to validate the final number of clusters. Therefore, a non-hierarchical, iterative clustering (K-means algorithm) was applied to assign individual observations to the previously determined cluster groups. With such clustering and validation method 99% of the individual cases could be classified into two exploratory pattern clusters. These patterns were labelled *axial* (n = 11) and *circular* (n = 28) based on their visual appearances (Figure 7).

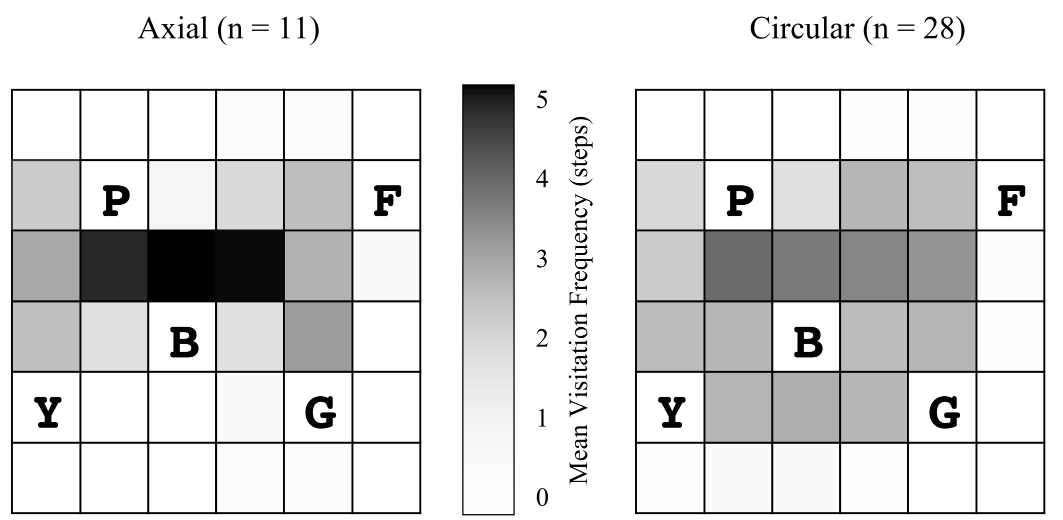


Figure 7. Two exploration patterns were identified in the physical space. Axial explorers (left) used a single main route to explore the objects, whereas circular explorers (right) used multiple routes and explored more extended spatial areas. The gray shadings correspond to the mean visitation frequency of each grid square. The upper bound (i.e., black square) of the visitation frequency was 5 steps. The objects inside the boxes are labelled as P=puffin; B=ball; G=gorilla; F=frog; Y=yellow bird.

Navigation Performance

Two efficiency measures of navigation performance were calculated for each participant during Phase 3:

- *Memory efficiency measure* was the sum of those individual squares that were entered at least once in this phase. This represented the cognitive cost of navigation and it was a function of the size of the physical area that was learnt and mentally represented. Memory efficient navigators learnt only a limited number of routes to keep the cognitive costs low. The highest memory efficiency (lowest cognitive cost) was associated with the smallest numerical value of this measure.

- *Distance efficiency measure* was the sum of the each square visit in the navigation test. It was the index of the physical cost of travelling or total route length. An increased score reflects more distances travelled, thus less efficient performance, whereas lower scores can be associated with shorter, more distance efficient routes.

A 2 (pattern: axial, circular) x 2 (efficiency: memory, distance) mixed model analysis of variance (ANOVA) was performed on the navigation cost as a dependent variable. Although distance efficiencies were normally distributed (p = .07), the memory efficiencies were not, $K(39, N = 39) = .21$, $p < .001$. Therefore, non-parametric tests were used for the *post hoc* interaction analysis. The applied omnibus F tests were robust enough to allow this type of violation to the normality assumption without invalidating the results (Morgan & Griego, 1998).

Significant main effects were revealed for exploration pattern, $F(1,37) = 6.29$, $p < .05$, partial $\eta^2 = .15$ and navigation efficiency, $F(1, 37) = 7.29$, $p < .05$, partial $\eta^2 = .17$. The Pattern X Efficiency interaction was also statistically significant, $F(1, 37) = 38.36$, $p < .001$, partial $\eta^2 = .51$ (Figure 8).

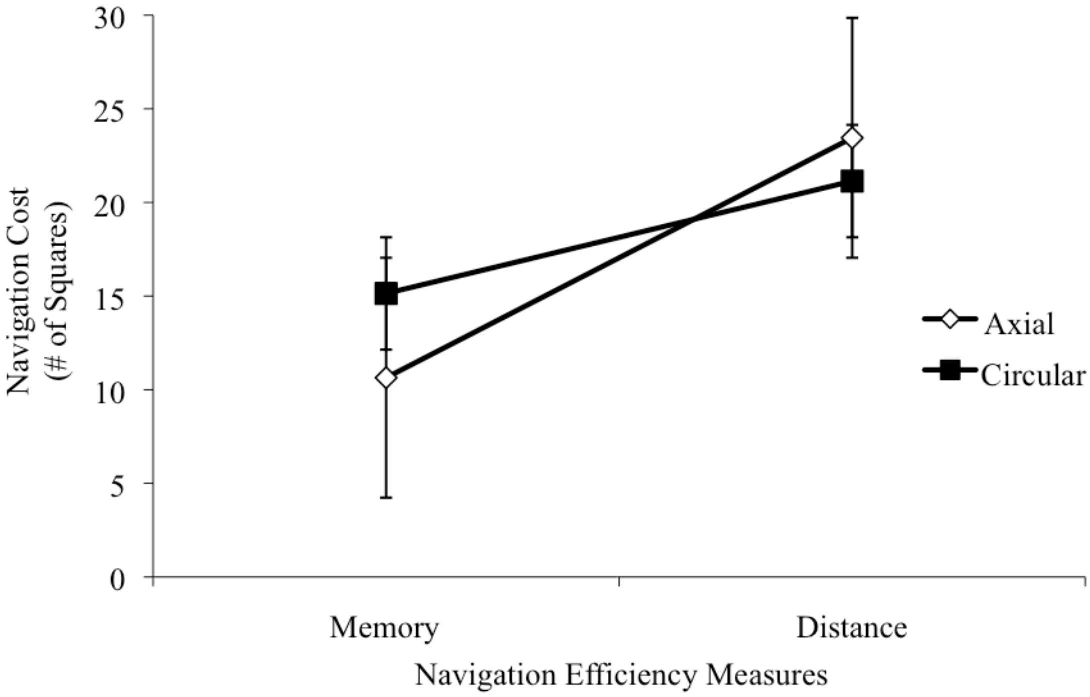


Figure 8. Significant interaction between measures of spatial navigation efficiency (memory & distance) and navigation costs by the two exploration pattern groups (axial & circular).

Due to the violation of the normal distribution assumption, in order to examine the interaction, two separate Mann-Whitney *U* tests were computed on the dependent variable. These analyses suggested that according to the memory measure, axial explorers were more efficient navigators with fewer number of squares entered (M_{axial} = 10.64 squares; SD_{axial} = 1.86) than circular explorers ($M_{circular}$ = 15.14 squares; $SD_{circular}$ = 1.46), U = 12.00, W^2 = 78.00, $z = -4.49$, $p < .001$. According to the distance efficiency measure, however, the circular explorer group was more efficient in their navigation, as they travelled less overall distance ($M_{circular}$ = 21.14 squares; $SD_{circular}$ = 2.93) than axials (M_{axial} = 23.45 squares; SD_{axial} = 3.42), U = 98.00, W^2 = 504.00, $z = -1.76$, $p < .05$ (Figure 9).

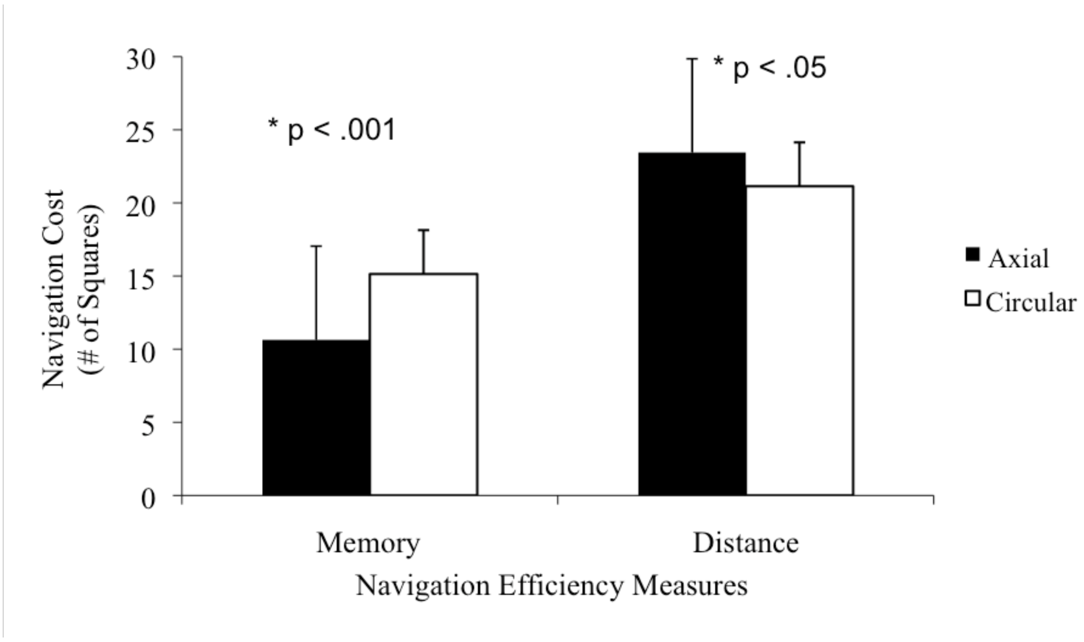


Figure 9. Comparison of navigation costs in Phase 3 between axial and circular explorers according to the two different navigation efficiency measures (memory & distance). Axial explorers were more memory efficient navigators as they solved the navigation tasks on fewer routes compared to the circular explorers. In contrast, circulars were more distance efficient navigators with shorter total distances travelled during the same task than axials.

The results were further analysed to examine possible gender effects. The proportion of males and females in each exploration pattern group was the same $\chi^2(1, N = 39) = 2.52$, $p = .11$. In terms of the navigation performances, the memory efficiency measure showed no gender effect, U = 174.00, $W^2 = 294.50$, $z = - 0.16$, $p = .87$, however, the distance measure revealed that males ($M_{male} = 19.80$ squares, $SD_{male} = 2.18$) solved the navigation task using shorter routes than females ($M_{female} = 23.04$ squares, $SD_{female} = 3.14$), U = 67.50, $W^2 = 187.50$, $z = - 3.27$, $p < .05$.

Discussion

The present study investigated navigation task efficiency as a function of initial exploration in a novel physical space. Two distinct clusters of exploration patterns (axial and circular) were found based on their emergent visual appearance. The results showed that search patterns reflect different strategies of spatial information acquisition and representation that determined the efficiency of subsequent navigation. Furthermore, the significant interaction in the data suggested that navigation efficiency depends not only on initial exploration patterns, but also on how optimal performance is defined.

The method used in this study to classify the exploration patterns represents a novel approach. The principle of this technique is based on artificial intelligence research of wayfinding trajectory analysis (e.g., Sas et al., 2005). However, the derived clusters in previous studies reflected only probabilistic categories based on the global visual features of the travelling paths and they were not necessarily meaningful in their functions (Thinus-Blanc & Gaunet, 1997). In contrast, the initial exploration patterns reported here reflect on functional roles (i.e., spatial strategy optimization between cognitive and behavioural costs of navigation) as they had a subsequent effect on navigation task performance. In fact, these two initial patterns determined navigation efficiency, indicating that the participants of each group used distinct spatial strategies when travelling through the physical space.

The axial group (left of Figure 7) was exploring only a limited region of the space, without expanding their search area. The explorations were mostly registered on the two main axes of the room and focused around these artificial lines of the room geometry. This pattern indicates a cognitively economical, route-following spatial strategy. Axial explorers preferred to follow these few routes, where object sequences could be represented with less cognitive cost on a fixed sequence rather than on a more complex survey representation (Hartley et al., 2003; Siegel & White, 1975). This strategy, however, resulted in higher travelling costs, as they had to make more journeys on fewer routes to perform the navigation tasks.

Circular explorers (right of Figure 7) spread out to the more peripheral regions of the space and included more closed trajectories around the centre of the room. This group initially explored the space more intensively, which could have resulted in more flexible spatial representations. The circular exploration pattern reflects a spatial strategy with higher cognitive costs, which in return allows more distance efficient navigation via more flexible route choices compared to axial explorers (Hartley et al., 2003).

Optimality of spatial navigation performance can be evaluated in at least two different ways, depending on whether the cognitive memory or the behavioural travel costs are taken into consideration. In this experiment these two approaches were represented by the memory and distance measures and the results were analysed both ways. The significant interaction between the two efficiency measures and the exploration patterns underlines that optimal performance is not an absolute measure and it depends on how efficiency is defined (i.e., based on the cognitive or on behavioural costs).

There is a relationship between the level of task complexity and the optimization of the spatial strategies (Hartley et al., 2003). In complex navigation tasks, where inferential relations have to be represented (i.e., the cinema is in the downtown, a few blocks away from the central library), a flexible exploration strategy could enhance wayfinding accuracy and efficiency. In such cases, reasonable cognitive effort has to be made to compute a novel route or select a more suitable previously learnt path. However, if the task is easy enough to be solved by the use of only simple action-based representations, a more rigid and routine series of navigation (i.e., following a few axial routes) could lead to a good level of performance. In such cases, simple associative links are sufficient for learning most of the spatial relations and reinforce one route as a reference to salient features of the space (Prados & Redhead, 2002). This route will then provide a simple solution in situations of navigational decisions (i.e., how to visit objects in one efficient way) with enough accuracy to find the destination and any extra cognitive load would rather disturb the execution of well-learnt route following. In simple tasks, a sequential solution could provide the best strategy with the most efficient routes. However, relying only on a single route for more complex navigation tasks could reduce the chance of finding the most optimal way.

In fact, humans seem to apply more than one strategy for orientation and wayfinding, depending on both environmental and individual factors (Lawton, 1996). This flexibility and range of strategy representations has its drawback when an inappropriate strategy is chosen, and when a simple solution provides efficient behaviour. The present study found that humans applied more than one strategy to explore novel spatial layouts, as they either used the geometrical axes of the room (axial), or a more spread and circular pattern (circular). Spatial strategies can be described and understood through the exploration patterns. The actual shape of these patterns depends on how behavioural and cognitive costs are allocated within the specific task environment and might vary in other spaces. Recent studies of spatial learning showed that the local features in an array of spatial landmarks could be determinant for place learning (Esber, McGregor, Good, Hayward, & Pearce, 2005). The configuration of the objects in our experiment could have induced more centre-based patterns, as one of the five boxes was in the centre of the space. Further studies are needed to investigate the role of spatial arrangement on the efficiency of navigation strategy patterns. Similarly, further investigations are required to decide whether the utilization of a particular strategy could increase spatial efficiency or individual cognitive decision-making styles have a more significant role in spatial knowledge acquisition. The questions will be addressed in the following chapters of this thesis.

Finally, the difference between men and women spatial performances need to be mentioned as navigation is reported to be sensitive to gender related factors (for a review, see Maguire et al., 1999). Males are often found to be better in mental image maintenance and manipulation, whereas females have more rapid access and retrieval capabilities in spatial tasks (Loring-Meier & Halpern, 1999). In the present study, there was no difference between the exploration patterns of males and females only between the overall travel distances. This suggests that spatial strategies are similar in the two genders and differences in performance are due to other variations in information processing. It is beyond the scope of the present work to fully investigate the question of gender in spatial strategies; however, these effects will always be included as a covariate in future analyses of this thesis and discussed respectively.

Chapter Summary

In summary, the first empirical chapter in this thesis found two distinct exploration patterns of a novel physical space. These initial patterns determined subsequent navigation efficiencies and represent different spatial strategies. The axial pattern is optimised for minimal cognitive effort by exploring and remembering objects on a fixed sequence of fewer routes over the expense of longer overall travelling distances. In contrast, circular explorers with more flexible spatial knowledge and consequently higher cognitive costs were able reduce their physical travel costs. The findings suggest a spatial strategy optimization trade-off between memory demands and distances travelled. At this point, however, it is an open question why individual navigators choose to optimize their routes according to these spatial strategies. A follow-up study presented in the next chapter was aimed to address this question.

Chapter 3: Always follow the Yellow Brick Road: The effect of forced exploration on navigation efficiency

It was demonstrated in the previous chapter that individual exploration of novel physical spaces involves an intertwined cognitive and behavioural optimization between the associated memory demands of route-planning and the physical costs of travelling distances. The allocation of these resources sets the basis of spatial strategies that determine the efficiency of further interactions with the environment. Spatial strategies therefore represent trade-offs in the cognitive system of how to explore and utilize optimally the available environmental resources. Participants were classified into two groups based on their exploration patterns (axial & circular). Axial explorers were more memory efficient navigators by exploring and remembering objects on a fixed sequence of fewer routes, whereas circular explorers were more distance efficient with less overall travels. The trade-off between the memory and distance spatial strategies was explained as an interactive cost/benefit adaptation of the individual explorer to the spatial environment.

It is not clear from this previous study, however, whether these spatial strategies are determined by the limitations of the spatial environment as opposed to individual navigation styles. The current follow-up study therefore examines whether an experimental manipulation to the exploration route (i.e., forcing the individual to explore exclusively on a set route pattern) changes the efficiency of subsequent navigation tasks. If individual styles were more dominant than the constraints of the exploration paths then forced learning should have no or little effect on performance. In contrast, if the path determines exploration then individually preferred patterns are overwritten by the experimental manipulation. Alternatively, it is possible that environmental factors interact with individual exploratory styles on a more complex level. In this latter case, a forced learning that is inconsistent with the individually preferred patterns would more severely affect performance than in a consistent learning condition.

After identifying initial exploratory patterns in an unconstrained environment, the present study forced participants to re-explore the space on either matching or conflicting exploration patterns. The participants were instructed to follow the yellow coloured carpet tiles (‘Yellow Brick Road’, YBR) laid on the floor to match a circular or axial exploration pattern. Finally, when the YBR was removed, the participants were required to navigate to sequences of objects. Efficiencies – similar to the first experiment – were quantified by measuring both the extendedness of the navigation routes (memory measure) and the overall travel lengths (distance measure).

Method

Participants

Thirty-two University of Southampton undergraduate students took part in the study (n = 32), 16 male and 16 females. Ages ranged from 18 to 26 years (M = 20.12, SD = 1.83). All our participants were non-paid volunteers and received course credits for their participation. They gave informed written consent in accordance with the School of Psychology research ethics committee.

Apparatus

The experimental room was the same physical space as in Chapter 2, except that the objects in Phase 1 of this experiment were familiar everyday objects (i.e., shoe, hat, tie, belt, coat) and the layout of the boxes was rotated 90-degrees (see Figure 10). In Phase 2 and Phase 3, the original set of soft toys (i.e., puffin, ball, gorilla, frog, yellow bird) and original layout were used. The change in the objects and the rotated layout for Phase 1 of this experiment minimized potential learning transfers between Phase 1 and Phase 2. However, because both the spatial relations and distances in the room were congruent with the ones in the previous study, direct comparison of the exploration patterns could be made between the two studies.

To force the participants to follow specific exploratory patterns (axial/circular), one of two arrangements of 50 x 50 cm square yellow carpet tiles were laid on the floor (YBR). The YBR either formed a single axial route with 8 tiles or a circular and spatially extended pattern made out from 12 tiles. Both YBR allowed access to all boxes. For a schematic layout of the different object locations and the YBR on the floor see Figure 10.

Procedure

Phase 1 (free exploration) was the same as in the previous experiment, except that the everyday objects were used in the 90-degree rotated layout (Figure 10). In Phase 2 (forced exploration), the objects within the boxes were changed to the set of soft toys and the layout was the same as in the previous study. The sequence of object visits was also the same, but participants were asked to travel exclusively on the YBR marked routes. Finally in Phase 3 (navigation task), the YBR was removed from the floor but the layout of the boxes and their contents remained the same. The instruction and sequence were identical to the previous study.

Results

Exploration Patterns

The transcription of the video recordings and the clustering algorithm followed the details of the previous study. The consistency between the transcribed datasets of the two researchers was over 95%. For the dendrogram of the hierarchical cluster analysis in this study, see Appendix B.

Similarly to the previous study, after the hierarchical clustering, a confirmatory non-hierarchical (K-means) cluster analysis was performed. Two initial exploration patterns (axial & circular) emerged in Phase 1 (see top part of Figure 10). Initial axial explorers (n = 8) stayed on a single linear route and walked repeatedly on only a few numbers of squares. In contrast, initial circulars (n = 24) explored a large number of squares and multiple routes between objects.

In Phase 2, participants were randomly assigned to either forced circular (n = 15) or forced axial group (n = 17). This created four groups with 12 participants in ‘C-C’ group with both the initial and forced circular patterns; 5 participants in ‘A-A’ group with both initial and forced axial patterns; 12 participants in ‘C-A’ group with initial circular and forced axial; and finally 3 participants in the ‘A-C’ group with initial axial and forced circular patterns (see Figure 10).

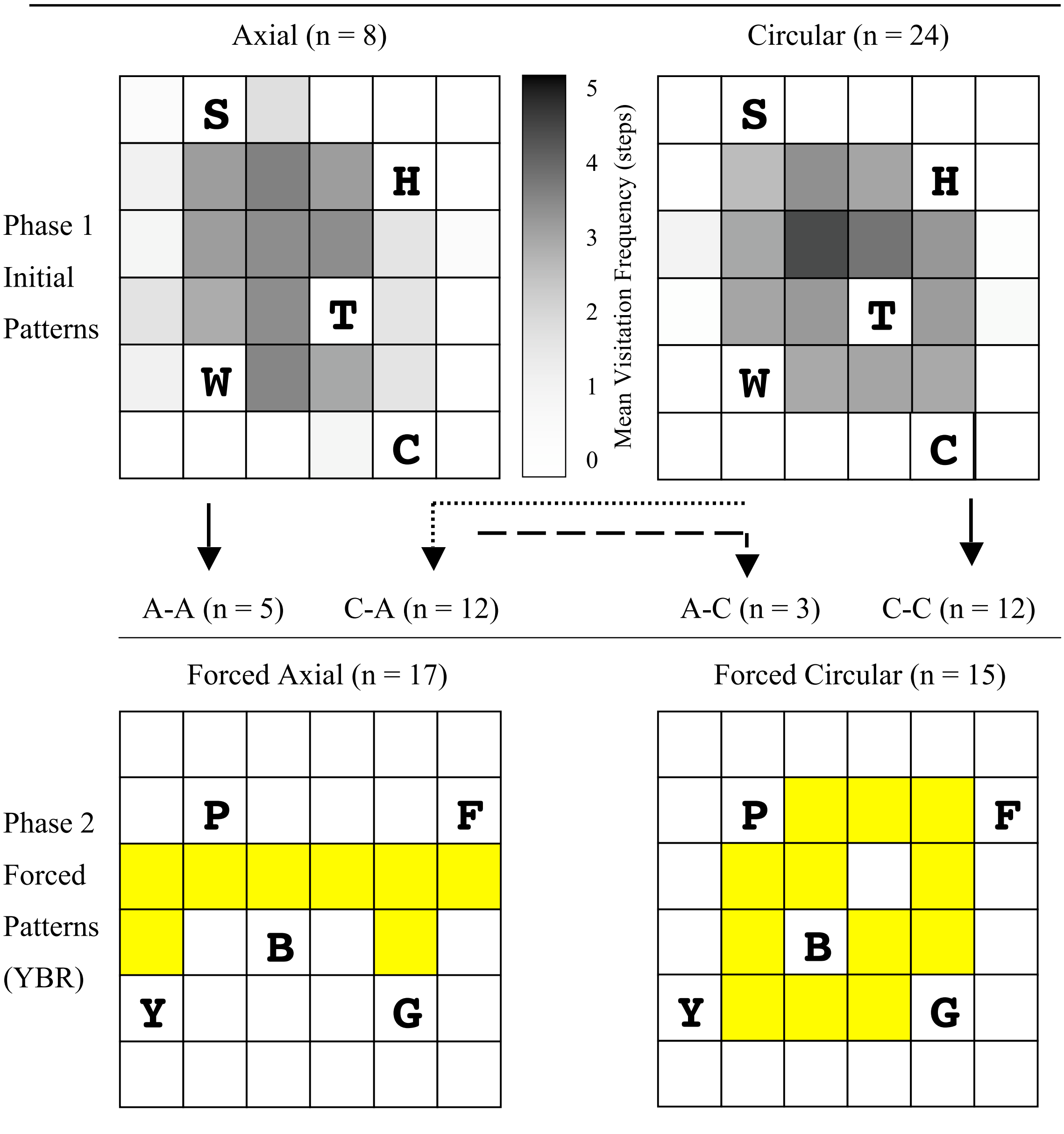


Figure 10. Top part shows the two initial exploration patterns (axial & circular) during free exploration of the 90-degrees rotated layout in Phase 1. The gray shadings correspond to the mean visitation frequency of each grid square. The upper bound (i.e., black square) of the visitation frequency was 5 steps. The first set of objects in the boxes are labelled as S=shoe; H=hat; T=tie; W=waistband; C=coat. Bottom part shows the two Yellow Brick Roads (forced axial & forced circular), where participants were forced to explore in Phase 2. The second set of objects are indicated as P=puffin; B=ball; G=gorilla; F=frog; Y=yellow bird. Participant subgroups are indicated according to their initial and forced pattern combinations (A-A: axial&axial; C-A: circular&axial; A-C: axial&circular; C-C: circular&circular).

Navigation Performance & Sub-Group Differences

Similarly to the previous experiment, two efficiency measures of navigation performance were calculated (memory & distance). To examine the effect of initial versus forced exploration patterns on navigation efficiency, two independent factorial analyses of covariance (ANCOVAs) were computed, one with the memory measure, and the other with the distance measure as dependent variable and – because gender effects were found in the previous experiment – with gender as a covariate. The dependent data was not normally distributed in the initial circular group, $K(24, N = 24) = .29$, $p < .001$; in the forced axial group, $K(17, N = 17) = .37$, $p < .001$; and in the forced circular group, $K(15, N = 15) = .29$, $p < .05$.

The first 2 (initial patterns) x 2 (forced patterns) factorial ANCOVA with the *memory* efficiency measure as dependent variable and gender as covariate revealed a significant main effect of forced patterns, $F(1, 27) = 4.73$, $p < .05$, partial $\eta^2 = .15$, but no main effect of initial patterns, $F(1, 27) = .09$, $p = .77$, partial $\eta^2 = .00$, no gender effect, $F(1, 27) = 1.40$, $p = .25$, partial $\eta^2 = .05$, nor interaction, $F(1, 27) = .02$, $p = .87$, partial $\eta^2 = .00$. The main effect of forced patterns showed that forced circulars visited the objects on significantly less spatially extended routes ($M = 13.53$, $SD = .74$) than participants in the forced axial group ($M = 14.94$, $SD = 1.78$). Thus, forcing the participants to follow a circular exploration pattern results in more memory efficient navigation (Figure 11). The fact that there was no interaction between initial and forced patterns suggests that forced exploration overwrites the expected effect of initial patterns on the cognitive costs of navigation efficiency. So even if the participants were initially axial explorers, forcing a circular pattern still resulted in more memory efficient navigation. Conversely, forcing an initially circular explorer to re-explore axially resulted in less memory efficient navigation performance. The results also showed that there are no gender related issues in the cognitive cost optimization, as the gender covariate analysis was not significant.

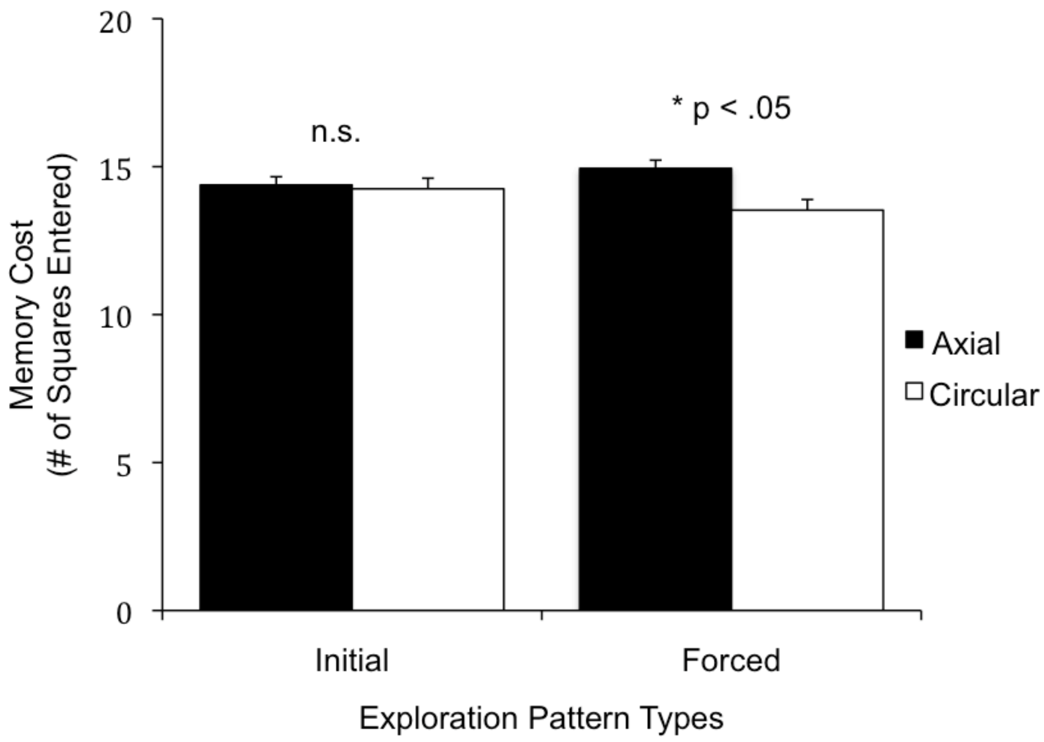


Figure 11. Comparison of memory costs in the navigation tasks (Phase 3) between initially preferred (Phase 1) and subsequently forced (Phase 2) exploration patterns. According to the initial patterns there was no difference in memory cost optimization. In contrast, forced circular explorers were more memory efficient navigators (with less memory cost) as they solved the navigation tasks on fewer routes than forced axials.

Although the interaction between the initial and forced patterns was not significant, due to the violation of the normal distribution assumption, simple effects were computed between the four pattern sub-groups (C-C, A-A, C-A, A-C). This was aimed to decide whether the effect of forced exploration was independent of initial patterns. Mann-Whitney U tests revealed that the C-C group was more memory efficient than the A-A group (U = 10.00; $W^2 = 88.00$, $z = -2.20$, $p < .05$) and the C-A group (U = 27.50; $W^2 = 105.50$, $z = -2.69$, $p < .05$). No other combination of subgroup comparisons was significant (i.e., C-A with A-A, $p = .59$; C-A with A-C, $p = .09$; and A-A with A-C, $p = .12$). The group means and standard deviations are presented Table 1. This analysis suggests that regardless of the initial exploratory patterns, forced circular patterns (x-C) resulted in better memory efficiency than forced axials (x-A).

Table 1
Means and Standard Deviations of the Navigation Performance Measures in the Yellow Brick Road Study.

	Initial (Phase 1)		Forced (Phase 2)		Subgroup (Initial x Forced)			
	Circular	Axial	Circular	Axial	C-C	A-C	A-A	C-A
N	24	8	15	17	12	3	5	12
Memory measure								
Mean	14.25	14.38	13.53	14.94	13.50	13.67	14.80	15.00
SD	1.70	1.06	.74	1.78	.80	.58	1.10	4.18
Distance measure								
Mean	71.25	72.25	71.20	71.76	71.08	71.67	72.60	71.42
SD	8.74	8.01	6.99	9.76	7.62	4.73	10.04	10.08

Interestingly, the second factorial ANCOVA with the *distance* efficiency measure as dependent variable found no significant main effects of either forced patterns, $F(1, 27) = .03$, $p = .87$, partial $\eta^2 = .00$, initial patterns, $F(1, 27) = .09$, $p = .77$, partial $\eta^2 = .00$, gender, $F(1, 27) = .06$, $p = .80$, partial $\eta^2 = .00$, nor significant interaction, $F(1, 27) = .01$, $p = .91$, partial $\eta^2 = .00$. Both forced circulars ($M = 71.20$, $SD = 7.00$) and forced axials ($M = 71.76$, $SD = 9.76$) – regardless of their initial patterns – used equal distance routes during their navigation tests (Figure 12).

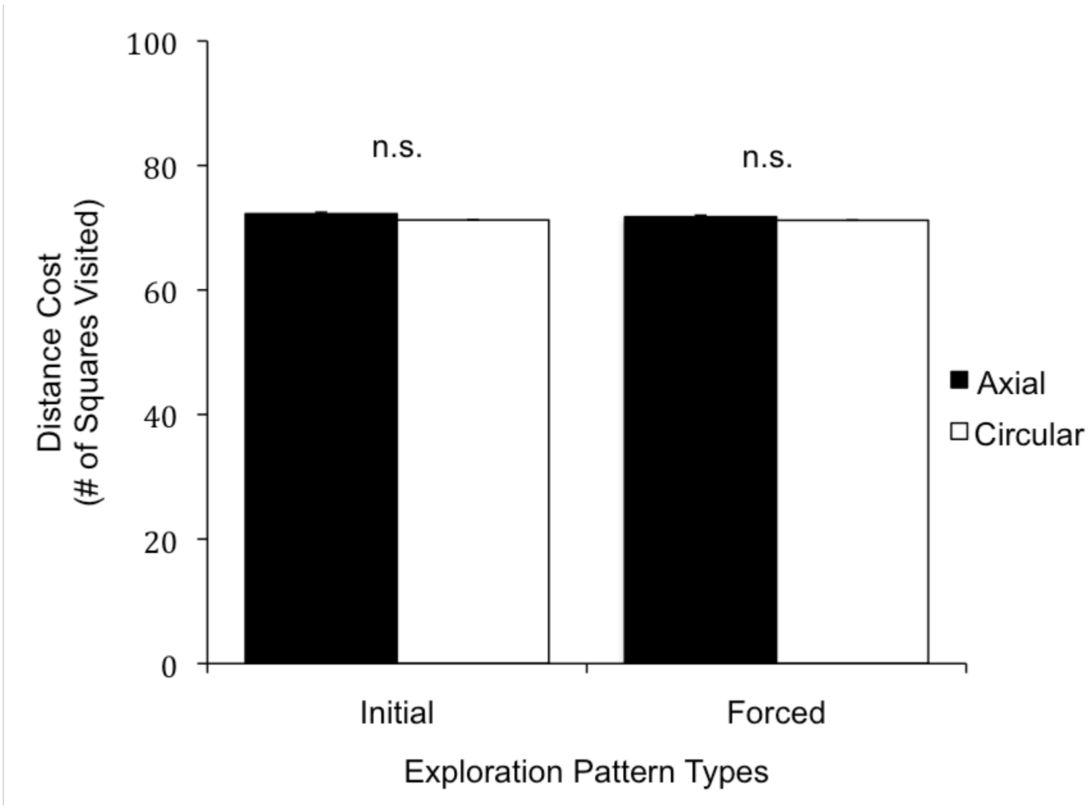


Figure 12. Comparison of distance costs in the navigation tasks (Phase 3) between initially preferred (Phase 1) and subsequently forced (Phase 2) exploration patterns. Neither in the initial nor in the forced condition did the axial and circular exploration groups differ in their travel distance optimizations.

Discussion

The aim of this follow-up experiment was to understand the effect of forced exploration on navigation performance through investigating whether spatial strategies are more constrained by the environment or by individual navigation styles. After identifying their initial exploration patterns, the participants were forced to re-explore a congruent space on fixed routes that either matched or were in conflict with their individually preferred spatial strategies. The results showed that forced exploration overwrites how efficiently participants remember routes, but not how much distance they travel. Overall this suggests that the cognitive aspect of spatial strategies is more sensitive to the task environment than to individual differences, whereas both equally affect the behavioural aspect.

As expected, participants were initially exploring the room on either an axial or circular patterns, according to their individual preferences. One third of the participants were initially axial and two thirds initially circular. This ratio replicates previously reported distributions of exploration patterns (Makány, Dror et al., 2006; Makány, Redhead, et al., 2007). It also demonstrates the prevalence of spatial exploratory patterns across studies of similar environments to be comparable.

The efficiency measures revealed interesting differences between the previous experiment in Chapter 2 and this follow-up. In the previous experiment, the axial explorers were more memory efficient, while the circulars were more distance efficient. In contrast, this time the forced circular explorers were the memory efficient navigators and the two groups travelled equally long distances, regardless of their initial pattern of exploration. To understand the mismatch in the memory efficiency, it is important to emphasise that although both patterns offer access to all objects, the circular pattern allows the explorer to learn the route knowledge flexibly, whereas the axial reinforces a single path. The difference is that a forced pattern is not the result of a spatial strategy, but it is a restrictive experimental manipulation. In other words, forced explorers lacked the control over their spatial strategies. In this study, the manipulation was the size of the YBR (8 or 12 squares respectively for axial and circular patterns) and the two forced groups had to explore the space on these restrictive patterns. Consequently, forced axial participants acquired only limited route knowledge, whereas forced circulars on the larger space had more flexibility of routes. This resulted in reduced memory efficiency for the forced axials, who then ‘roamed’ to unexplored routes during navigation that were not accessible for them during the forced exploration phase. These extra routes could have decreased their memory efficiency. Forced circular explorers, on the other hand, with the more extensive route knowledge did not need to deviate from the already explored routes. This in return increased their memory efficiencies as they could select the optimal navigation route prior to the physical travel.

Interestingly, neither in the initial nor in the forced condition did the axial and circular explorers differ in their travel distance efficiencies. Compared to the previous study, where circulars travelled less distances during the test, fixed exploration routes in the YBR-experiment balanced out such differences of spatial strategy optimization. The lack of a significant difference in this follow-up could be attributed to the limited sample size of the current experimental design. The 32 participants tested in four subgroups might not have provided sufficient statistical power for the analysis. Testing additional participants, especially in those groups with the lowest sample sizes (i.e., initial axial), could rectify this problem. This would be especially beneficial, as the trend in the data is in line with the results of the first experiment.

This research could also help understanding how other physical spaces with guiding routes might influence human spatial behaviour through different degrees of controlled navigation aids. There can be numerous real world applications including design considerations of large department stores (Penn & Turner, 2001) or urban planning (Hillier, 1996). For example in 2003, the Swedish furniture retailer, IKEA, introduced a new store layout in Toronto, Canada because the company thought that their usual maze-like design concept with the yellow road showrooms "fuels impulse buying as customers are lead through several departments" (Retrieved December 12, 2008, from http://www.allbusiness.com/retail-trade/miscellaneous-retail/4430896-1.html). The new store layout with a central corridor and side aisles is hoped to "lessen the confusion while still driving customers through the store" (¶ 1). Although the business interests of companies like IKEA in forced explorations could be slightly more diverse than naïve scientific questions (i.e., making or helping lost customers in stores), considerations to the human cognition and spatial strategies could result in financial benefits and better customer satisfaction.

In summary, this follow-up study found that humans only optimize their spatial strategies, and choose between a memory or distance efficient navigation, when their spatial environment provides them with a certain level of control over their exploration patterns. If, however, the space is restrictive, as it was the case with the YBR, the limitations of the task environment overwrite individually preferred spatial strategies and navigators adapt to the externally forced spatial strategy optimization.

Chapter Summary

The experiment presented in this chapter found that forced exploration patterns changed the expected memory optimization strategies of the participants. However, the current study did not find a trade-off between cognitive memory and behavioural locomotor resource allocations. I proposed that the lack of control over their spatial strategies could have been accountable for this, as forced learning might have disturbed the individually preferred resource allocations of the cognitive system. In a possible future modification of the current paradigm, participants could be provided with the YBR without explicitly asking them to follow the pattern. This way, they may implicitly adopt the forced routes and optimize between the memory and distance resources similarly as in an unconstrained environment.

The main finding of this chapter was that environmental constraints influence spatial strategy optimizations. The next chapters will continue exploring this theme in more details by creating abstract spaces where the cognitive and behavioural navigation costs can be experimentally manipulated. The first example in Chapter 4 will be a virtual environment, where the physical travel cost is zero.

Chapter 4: Strategies of spatial memory and travelling distance resource optimization in a virtual space

Exploration of a cluttered virtual environment (VE) requires the navigator to move around a computer-generated space with the specific aim of avoiding or approaching virtual objects (Ruddle & Jones, 2001). In general, simpler VE interfaces provide easier and more efficient movement options for navigation than complex ones (Lessels & Ruddle, 2005; Ruddle & Jones, 2001). Apart from the limitations of the task environment, other factors such as the individual differences have been previously reported to influence performance in a VE (for a review, see Sas, 2004). For example, variability in the inter-individual use of the most efficient navigational strategy was recently supported by evidence from brain imaging studies (Etchamendy & Bohbot, 2007; Hartley et al., 2003; Iaria, Petrides, Dagher, Pike, & Bohbot, 2003). Participants of virtual navigation tasks either used a landmark-based wayfinding or a response-based route-following strategy. The efficiency of these strategies was strongly related to the cognitive requirement of the task environment (Etchamendy & Bohbot, 2007). While travelling around a virtual town, for example, the spatial strategy that utilizes external landmarks and multiple routes between them is more efficient than a single well-known route-following directed by egocentric turning directions. However, in other tasks, like in radial arm or starmazes, the two navigational strategies could yield similar performance results in terms of the visited areas, speed or accuracy (Iglói et al., in press). Moreover, fMRI results showed that wayfinding strategy only activates the hippocampus, while the caudate nucleus is firing during route-following (Hartley et al., 2003). These neuro-cognitive studies indicate that when examining spatial navigation and wayfinding performances in a VE, both the specific task demands and individual strategy preferences need to be considered.

The human cognitive system adaptively responds to the informational processing demands of interactive environments (Anderson, 1991). Individuals allocate their available cognitive and behavioural resources based on a series of cost/benefit trade-offs (Gray & Boehm-Davis, 2000; Gray, Sims, Fu, & Schoelles, 2006). Optimal performance in spatial cognition means to maximize the difference between the expected gains and related costs of goal-directed travelling. More specifically, this involves an optimization between wayfinding and locomotion (Chen & Stanney, 1999; Freundschuh, 2004). While the cost of wayfinding can be quantified as the cognitive effort of acquiring, remembering and planning routes in the space, the locomotor expense is the total distances travelled. Previous studies, including Chapter 2 and Chapter 3 in this thesis, suggested that behavioural strategy patterns emerge as a result of these spatial cost-benefit optimizations (Gaunet & Thinus-Blanc, 1996; González et al., 2008; Helbing et al., 1997; Hillier & Iida, 2005; Kállai et al., 2005; Makány, Redhead, et al., 2007; Sas et al., 2005). Moreover, these studies showed that spatial strategy patterns were reliable indicators for subsequent navigation performances. When the individual explorer travels through the environment the travelled routes not only record a history of how the environment was discovered, but also predict the efficiency of future navigations. If these routes are depicted on the map of the environment, it reports on the most frequently visited regions and on typical object exploration behaviours. Classification of these visitation patterns could reveal their underlying functions.

In a desktop VE, however, the locomotion cost of navigation is minimal as the participant is sitting in front of a computer screen and proprioceptive (body-based) signals are not accompanying the travel (Klatzky, Loomis, Beall, Chance, & Golledge, 1998). Thus, spatial strategies in a VE are more focused on the optimal cognitive representation of such abstract spaces than travelling the shortest distances. Previous studies confirmed this bias in the optimization trade-offs towards the cognitive costs of navigation by showing that people are more sensitive to cognitive overload in VE than in physical spaces (Klatzky et al., 1998; Ruddle & Lessels, 2006a; Waller, Hunt, & Knapp, 1998; Witmer, Bailey, Knerr, & Parsons, 1996).

The study presented in this chapter investigates the allocation of spatial memory and travel resources during spatial exploration of a desktop VE and its influence on performance levels in a subsequent navigation task. Furthermore, the results obtained in this VE will be compared to Chapter 2, which serves as a baseline experiment. The aim is to measure exploration costs and navigation benefits in a photorealistic desktop VE that is equivalent to the experimental room in the baseline study. Participants in the VE could first freely explore the virtual room containing five objects that needed to be explored from a close distance. The initial free exploration routes were analysed with a clustering algorithm. After an extensive training phase, whereby the object locations were learnt, the participants' final task was to revisit sets of objects in the most efficient order. The navigation routes in this last phase were measured for both their memory efficiencies (extendedness of the travelled routes) and distance efficiencies (total distances travelled).

It is expected that the same axial and circular exploration patterns, as observed in the physical environment (Chapter 2), would emerge in this equivalent desktop VE. These patterns give indication of the underlying spatial optimization strategies. Consequently, the initial patterns in this VE with the same layout as the physical space should be the same. However, the navigation efficiencies in the final task might be different in the desktop VE, where no body-based information is present. Compared to the physical environment where the locomotion of the whole body requires considerable behavioural resources, in a desktop VE such cost is minimal. This could result in a modification of the optimization strategies, whereby the focus of such trade-offs is biased towards the memory efficiency rather than on reducing total travel distances.

Method

Participants

Forty-one undergraduate students, 32 female and 9 male participated in the study. One female participant's data was erased due to a computer failure, which left a total of 40 participants for the analysis (n = 40). The mean age of the participants was 21.33 years (*SD* = 6.47) with a range of 18 to 56 years. All were non-paid students from the School of Psychology, University of Southampton and received course credits for their participation. Only participants with no or minimal previous experience with interactive computer games and other VE were recruited for this study to avoid potential bias (Waller, 2000).

The overrepresentation of female participants was due to the limited availability of males in this sample population. However, gender differences and potential sampling biases were controlled throughout the study.

Apparatus

The desktop-based VE in this experiment (Figure 13) was a simulation of the physical space used in Chapter 2 (Figure 2). The basic structure of the virtual room was created using 3D Studio Max software (Discreet, Montreal, CA). The floor, the walls, the ceiling and the five identical hollow box shapes were textured with photo images taken in the real room. The five boxes were positioned in the same irregular array. The relative sizes of the objects in the VE were proportional to the physical space. Each box contained an image of the same five soft toy objects as in the real room (puffin, ball, gorilla, frog, yellow bird). All the images of the objects were taken from the perspective from which they could actually be seen inside the boxes (Figure 6).

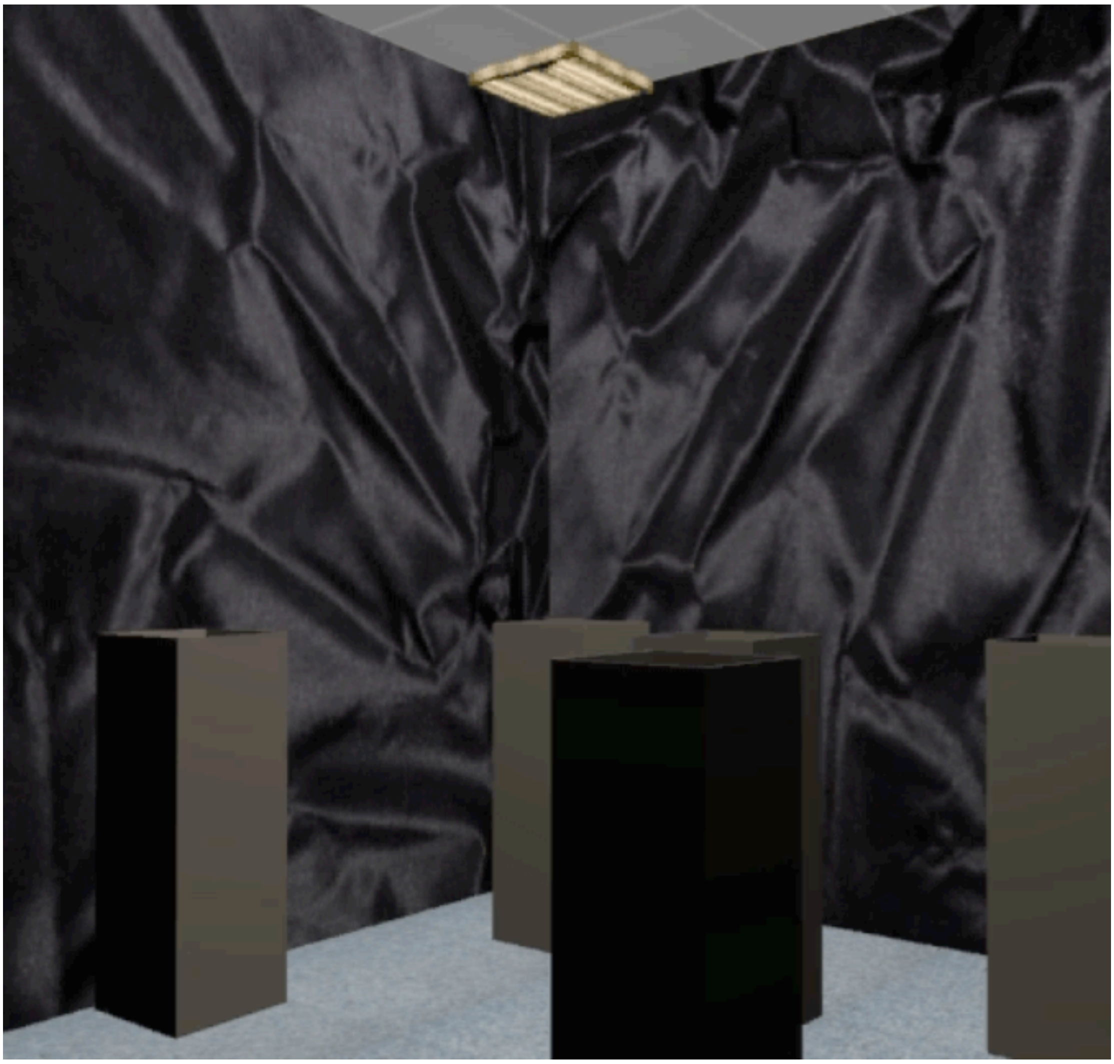


Figure 13. Screenshot from the VE showing the five boxes, the walls covered with black curtain, the floor and the neon light on the ceiling from the participants' perspective. This layout and the relative sizes of the objects were proportional to the physical space in Chapter 2. Participants could look into the boxes to explore the different soft toys inside by navigating close the edge of the box.

This virtual design was exported into the experimental software Presentation (version 10.1, Neurobehavioral Systems Inc.) and showed to the participants at a distance of 60 centimetres on a standard 17-inch desktop PC monitor with a screen resolution of 800 x 600 pixels. The starting position was fixed to the same entry point (near gorilla) and heading orientation (North) as in the real room across all trials. Participants navigated around the virtual environment using the arrow keys on a standard keyboard and they could look upwards or downwards by moving the mouse. The software recorded the spatial coordinates at each move. For the object visits, the participants were asked to press an assigned key to record which object was seen (puffin – P; ball – B; gorilla – G; frog – F; yellow bird – Y). Pressing a key in the VE was a necessary addition to the equivalent task in the physical room, as object visits could not otherwise be recorded. The computer software also registered spatial coordinates at each step.

Procedure

The procedure in the VE was identical to the procedure described for the physical space in Chapter 2. Following verbal instructions by the experimenter, participants pressed the space bar and the experiment started. After the last object was visited, the software terminated and the experiment ended.

Results

Exploration Patterns

Initial exploration patterns in Phase 1 were identified using the classification algorithm detailed in Chapter 2. Similarly to the previous studies, two initial exploratory patterns emerged. See Appendix C for the dendrogram of the hierarchical cluster analysis in this study. Before participants could be assigned to either of these groups, a confirmatory second (non-hierarchical, K-means) cluster analysis was performed. After this second step, the participants were identified into either axial or circular patterns (axial & circular; Figure 14).

The *axial pattern* (n = 16) explored the space sequentially and stayed in line with the geometrical axes of the room. The visual appearance of this pattern was linear with a high number of revisits to the same spatial locations. Axial participants only visited in average 12 squares during their exploration and they preferred a route-following spatial strategy with fixed sequence of object-to-object travels. This limited exploration behaviour represents a lower demand on the spatial memory system, as only a single route needed to be remembered.

In contrast, participants with a *circular pattern* group (n = 24) included round shape routes that spread out to the outer regions of the space. This group explored an extended spatial area with in average 22 different squares visited at least once during Phase 1. Circular pattern allowed the participants to learn a range of alternative routes between objects to utilize in subsequent wayfinding. Such an increased spatial knowledge represented relatively high memory cost on the cognitive system (see Hartley et al., 2003 for more details on the difference between route-following and wayfinding spatial strategies).

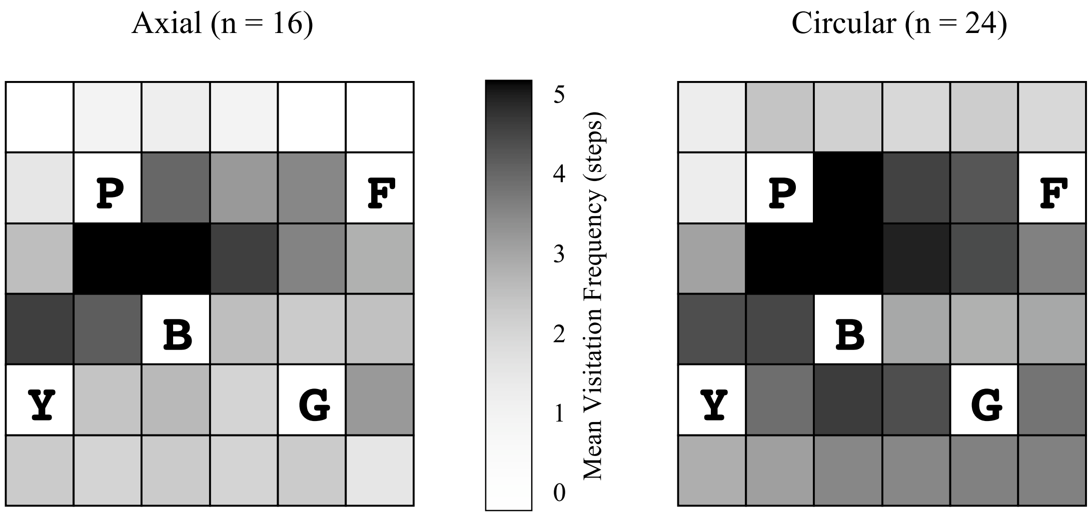


Figure 14. Two exploration patterns were identified in the virtual environment. Axial explorers (left) used a single main route to explore the objects, whereas circular explorers (right) used multiple routes and explored more extended spatial areas. The gray shadings correspond to the mean visitation frequency of each grid square. The upper bound (i.e., black square) of the visitation frequency was 5 steps. The objects inside the boxes are labelled as P=puffin; B=ball; G=gorilla; F=frog; Y=yellow bird.

The proportion of males (n_{axial} = 5 & $n_{circular}$ = 4) and females (n_{axial} = 11 & $n_{circular}$ = 20) in the two identified exploration pattern clusters was not significantly different, χ^2 (1, N = 40) = 1.17, *p* = .28. Additionally, as the sampling of males and females was non-equal a Cramer's V was calculated, V = .17, *p* = .28. This further confirmed that the disproportionate sampling of genders did not play a role in how participants were initially exploring the virtual environment.

Navigation Performance

In a similar manner to the previous chapters, two efficiency measures (memory & distance) were calculated. To analyse the effect of spatial strategies on navigation performance in the VE, a 2 (pattern: axial, circular) x 2 (efficiency: memory, distance) mixed model analysis of covariance (ANCOVA) on the navigation cost as a dependent variable with gender as a covariate was performed. The dependent variable measured according to the memory efficiency was not normally distributed, *K*(40, N = 40) = .22, $p < .001$. Therefore, non-parametric tests were used for the *post hoc* interaction analysis.

Significant main effect was revealed for navigation efficiency after controlling for the effect of gender, $F(1, 37) = 6.73$, $p < .05$, partial $\eta^2 = .15$, but no such effect was found for exploration patterns $F(1, 37) = 0.53$, $p = .47$, partial $\eta^2 = .01$. The Pattern X Efficiency interaction was significant, $F(1, 37) = 9.80$, $p < .05$, partial $\eta^2 = .21$.

To further examine the interaction, two separate, non-parametric Mann-Whitney *U* tests were computed on the non-standardized dependent variable. These analyses revealed that the axial explorers were more memory efficient navigators with fewer routes (M_{axial} = 17.31 squares, SD_{axial} = 1.74) than circular explorers ($M_{circular}$ = 18.46, $SD_{circular}$ = 2.09), U = 121.50, W^2 = 257.50, $z = -2.01$, $p < .05$. According to the distance efficiency measure, however, there was no difference between the overall travel distances of the two groups (M_{axial} = 26.00, SD_{axial} = 4.91, $M_{circular}$ = 25.13, $SD_{circular}$ = 4.15), U = 174.50, W^2 = 474.50, $z = -.49$, $p = .63$ (Figure 15).

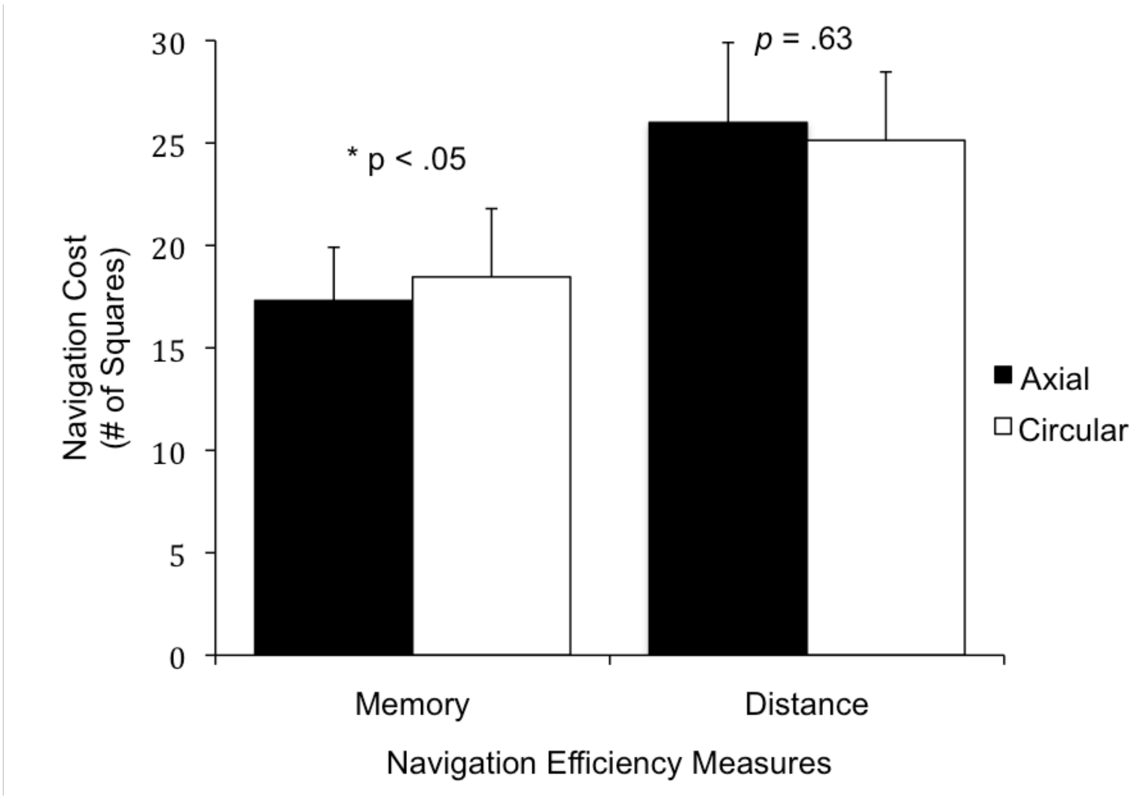


Figure 15. Comparison of navigation costs in Phase 3 between axial and circular explorers according to the two different navigation efficiency measures (memory & distance) in the VE. Axial explorers were more memory efficient navigators as they solved the navigation tasks on fewer routes compared to the circular explorers. In contrast, there was no statistically significant difference between the two groups in their travel distance optimizations.

Discussion

The present study investigated navigation task efficiency as a function of initial exploration in a photorealistic desktop VE that was equivalent to a physical space in Chapter 2. The primary aim here was to look at the effect of a VE on cognitive (memory) and behaviour (locomotor) resource allocations. The results demonstrated that although VE users initially explored the virtual space according to the same patterns (axial & circular) as in the physical environment, there were subtle differences in the optimization trade-offs of subsequent navigation task. Circular explorers – similarly to the first experiment – acquired a memory demanding, flexible, survey-type spatial representation of the VE, but they did not utilize their increased knowledge better than axials. In contrast, axials with a memory efficient, limited route-following spatial strategy achieved the same distance efficiency as circular explorers. This shows that in the present desktop VE, distance travelling has less weight on spatial strategies than the cognitive cost optimization.

These findings are in line with previous research suggesting that the cognitive demands of the task need more consideration in virtual navigation than in a physical space (Morganti et al., 2007; Ruddle & Lessels, 2006a). However, this study adds to current literature of navigation in a VE with the more detailed analysis of both the cognitive and the locomotory cost allocations. The cognitive cost of acquiring and remembering routes between landmarks was interacting with the cost of locomotion. Participants had to plan where to travel, remember where they had been and travel the required distances. The results showed that spending less cognitive effort on exploring and learning alternative routes and following a single route did not lead to suboptimal distance efficiency, as it was the case in the physical space. One possible explanation for this could be that VE present an effortless navigation space, where travelling has no considerable costs. Therefore participants might have altered their initial spatial strategies and rather travelled more than to mentally recalculate a route during navigation. This is supported by the fact that the distance efficiency measure was not different between initial circulars and axials.

When participants initially entered the VE, they explored the space on same two patterns (axial & circular) as participants in the equivalent physical world study in Chapter 2. This suggests that regardless of the space being physical or virtual, the participants interacted similarly at their first encounter. In the physical space, these initial cost/benefit optimization strategies lead to performance trade-offs. Participants of that experiment had either initially higher memory costs and subsequently solved the navigation tasks with shorter travel distances (circular explorers) or reduced spatial learning costs and worse distance efficiency (axial explorers). However, in this VE a different type of trade-off was found. While the circulars were still using more flexible routes, their distance efficiency was equal to the axials. In other words, users of a desktop VE initially explored and interacted with the virtual space the same way as in the physical space, but they changed their navigation strategies as a consequence of the effortless travel.

There are potential limitations to generalize the conclusions of this VE study. For example, three times more female participants took part in the experiment than males due to unequal availability in the sampling population at the time of the data collection. This could have biased the results as gender related differences are often reported in spatial cognition studies (for a review see Coluccia & Louse, 2004). To compensate for this, all data analyses reported in this study were controlled for gender effect (e.g., Cramer's V, ANCOVA). Another possible limitation was the lack of a social reference for our participants. In more realistic navigation situations, the effect of other travelling individuals adds significantly to the optimal resource-foraging behaviour strategies (Goldstone & Ashpole, 2004). To consider the social aspects of this work was beyond the scope of the present investigation. However, this line of research represents an attractive further research opportunity.

Chapter Summary

The presented study in this chapter has important implications for both the scientific understanding and applied aspects of navigation in a VE. First, the study indicates that the users of a desktop VE initially consider but subsequently exclude travel distance from their cost/benefit analysis of spatial navigation. Based on this study alone, however, the exact point of when it happens during spatial learning cannot be established. Further investigations are needed to map the temporal dynamics of spatial strategy optimizations. This is especially important as cognitive and behavioural resource allocation is considered a dynamic adjustment to a series of microstrategies rather than an all-or-nothing decision (Gray & Boehm-Davis, 2000; Gray et al., 2006). One way of testing this could be a modification of the present VE, where artificial costs could be associated with the virtual steps of the participant. Pre-allocating a finite set of 'energy points' to the participant might increase the relevance of distance optimizations. However, as Chapter 3 demonstrated, the effect of such forced exploration might overwrite the naturally occurring spatial strategies. Nevertheless, the presented analysis of the virtual exploration patterns gives good predictions for the subsequent navigation performances when the environmental effects – for example an effortless VE – are taken into account. Second, although circular explorers acquired detailed route knowledge about the VE, the extra spatial information was not exploited during the task. Well-planned instructional designs of future VE may be able to utilize this cognitive potential to improve navigation efficiencies. Third, understanding spatial navigation trade-offs in different spaces have relevance for scientific theory making and research. Most studies that reported similar performances between physical and VE neglected the cognitive/behavioural strategy interaction and came to a conclusion that the underlying mechanisms are the same in all environments (Kállai et al., 2005; Ruddle et al., 1999). However, the present study with a VE showed that users optimized cognitive resources similarly, but behavioural costs differently than navigators in the equivalent physical space. This subtle, nevertheless crucial difference of how the cognitive system interacts with different spaces should encourage future studies in this field to pay more attention to these trade-offs.

An extension to the present and previous studies is presented in the next chapter. The accumulated human data will be simulated in an agent-based simulation that models all combinations of spatial cost/benefit optimization strategies (for a similar approach in a multi-agent environment, see Turner & Penn, 2002). The model includes distance and memory efficiency parameters as complementary factors for navigational decisions. Previously inconclusive empirical findings as well as new research ideas from a range of spatial environments, including large-scale physical and VE, could be verified with such a model.

Chapter 5: An agent-based model of human exploration patterns: Optimization strategies and trade-offs between spatial memory and distance travelled

Humans are adaptive mobile agents with a high degree of temporal and spatial regularities within their wayfinding and navigation behaviour (Golledge & Stimson, 1997; González et al., 2008). In contrast to other foraging animals, whose individual search trajectories are approximated by models of random walk (Edwards et al., 2007; Sims et al., 2008; Viswanathan et al., 1996), human mobility patterns display more organised statistical features, indicating that these patterns emerge as a result of a few simple and identifiable spatial strategies. Examples include frequent revisits of salient locations (González et al., 2008), relying on the topological properties of the space in wayfinding (Hillier & Iida, 2005), or following existing trails (Helbing et al., 1997). Despite the sophisticated mathematical descriptions of human mobility patterns, the psychological mechanisms behind these strategies are still not well known. To understand the underlying functional mechanisms of spatial strategies, we have to look into how human cognition allocates cognitive memory and behavioural locomotor resources when interacting with the surrounding spaces (Anderson, 1991; Gray et al., 2006; Waldron, Patrick, Morgan, & King, 2007).

The rational analysis approach holds that human cognition is an adaptive complex system that helps the individual to respond optimally to the information processing demands of its environment (Anderson, 1991). Individuals interact with their task environments in terms of cost-benefit considerations over an expected utility of their behaviour. Optimal performance maximizes the difference between the expected gain and cost of mental and physical efforts. This rational optimization process explains trade-offs in systems such as the human memory, where the probability of finding the relevant memory (gain) should be always higher than the cognitive cost of the retrieval. In terms of spatial behaviour, the best navigators optimize their strategy use to fit the demands of the surrounding environment appropriately (Etchamendy & Bohbot, 2007).

Waldron et al. (2007) demonstrated how human cognitive strategies are determined by delicate cost-benefit trade-offs in a spatial memory task. Memory resource allocation during a routine copying task was measured as a function of information accessibility. It was found that when the cost of accessing information increased (for example, as a result of non-immediately available information), memory-intensive strategies were more often used in order to complete the task efficiently. Higher memory demands resulted in better retention performance, suggesting that more developed cognitive representations were created. Participants with high access cost spent more time encoding information (increased memory strategy), which resulted in less overall physical visits to the target patterns.

In most spatial tasks, there are many locally good routes to a specific target location, and although they could be very close to the shortest one, they are often very different both from the optimum and from each other (Charter & Oaksford, 1999; Makány, 2006). This can be explained by a refined version of the rational analysis, which argues that the allocation of cognitive and perceptual-motor resources is adjusted to a series of microstrategies based on temporal cost-benefit trade-offs (Gray & Boehm-Davis, 2000; Gray et al., 2006). According to these authors, most interactive behaviour, including spatial exploration, is not a result of an all-or-nothing decision. Instead, a mixture of locally optimal (e.g., least-effort) trade-offs determines their patterns. These patterns are subject to change by deliberately adopted policies or behavioural strategies, even if they result in sub-optimal solutions (Gray et al., 2006). Such strategy could be a top-down process, an individual preference or a learning programme, which could override the globally ideal cost-benefit optimization for a particular situation.

From the cognitive-behavioural point of view, the exploration of a novel space involves a dual task of planning routes for wayfinding and travelling physical distances (Chen & Stanney, 1999; Freundschuh, 2004). Consequently, the associated costs are also quantifiable as a mixture of the cognitive effort (planning and memorizing routes) and the locomotor expense (travelling certain distance). Although complex human foraging in a social context is influenced by additional factors, such as the strategies of other foragers (Goldstone & Ashpole, 2004), in situations where the exploration takes place in a non-social environment, the analysis of the cognitive and behavioural resources can lead to reliable results. For example, previous studies suggested that spatial strategy optimizations lead to identifiable exploratory route patterns, and that these patterns may predict spatial task efficiency (Gaunet & Thinus-Blanc, 1996; Kállai et al., 2005; Makány, Redhead, et al., 2007; Sas et al., 2005). However, there is little systematic understanding or formalized hypotheses of what could be the optimization mechanisms behind these spatial strategies.

The experiments in previous chapters presented participants with navigation tasks in the same highly stylized, physical or equivalent virtual spaces. The exploration patterns chosen by the participants exhibited statistical regularities. It was hypothesized that the underlying spatial strategies were based on simple heuristics predicated on informational benefits from the exploration of new spaces and perceptions of physical costs from distance travelled. This *memory-distance* (M-D) hypothesis is offered as a means of understanding the results of the laboratory studies. It has not, however, been formalized and explored as a hypothesis generating theory.

This chapter seeks to formalize the M-D hypothesis and test its ability to generate predictions that map to observed human behaviour in the previous chapters. The stylized empirical settings previously detailed in Chapter 2 present a unique opportunity to explicitly reconstruct this human laboratory experiment in a simulation modelling construction. The M-D hypothesis is formalised as a highly simplified decision function that guides an agent in navigating a two-dimensional computational model space. The resulting simulated navigational paths based on the M-D motivated agent are compared to the paths taken by the humans in the baseline study. Simulation sweeps across this two-parameter model will be analyses with differential weightings of memory versus distance strategy on the navigation task performance and efficiency.

Model and Experiment

Regular social scientific models begin with a theory from which a hypothesis can be formulated and empirically tested using data from either laboratory or natural experiments. The M-D hypothesis, however, is a product of a laboratory study (Chapter 2). The modelling process involved 'reverse engineering' to test whether a formal distillation of the hypothesis is capable of predicting behaviour similar to what inspired its original formulation. The final agent-based model (ABM) simulated human spatial exploration behaviour based on the two strategies (memory & distance) previously found in Chapter 2.

The model was coded and implemented within NetLogo, a freeware modelling environment (Wilensky, 1999). The code and a running JAVA applet are available on http://www.tamasmakany.com/html/public/SpatialABM.html. The model is completely self-contained, including procedures for parameter sweeps and data generation.

The ABM was comprised of a single artificial agent travelling in a computational model space. This space was a two-dimensional lattice divided into 6 x 6 square grids. It had the same spatial layout as the physical space in Chapter 2 and the target objects reside at identical locations (see top row of Figure 16). The starting position was fixed to the top left corner of the lattice, identical to the location of the entrance in the original experiment.

The first task of the agent was to explore all five objects. Because the agent could not step directly on a square containing an object, a visitation was administered when she stepped onto one of the adjacent empty squares. To determine which target location to visit next, the agent calculated an expected exploration cost for each path leading to a not yet visited location. This cost was a function of stepping on previously unexplored squares (memory cost) and the total number of squares it would take to get to the target (distance cost). See Equation 1. The agent was entirely myopic, without foresight, or the ability to rescind inefficient travel decisions. This simplicity of the decision-making heuristic falls comfortably under the rubric of bounded rationality (Simon, 1955).

$$f(C_e) = M_{i,j}^{\alpha} \times D_{i,j}^{\beta} \tag{1}$$

The expected exploration cost function $f(C_e)$ served as the objective function that the agent sought to minimize. The agent evaluated the costs for each space that was adjacent to an unvisited object, j, relative to her current location, i. The inputs in the function were the memory cost, $M_{i,j}$, and the distance cost, $D_{i,j}$, associated with the spaces that must be traversed between the two locations. $M_{i,j}$ was the sum of the those individual squares that were entered at least once between coordinates i and j. $D_{i,j}$ was simply the geometric distance between the Cartesian coordinates of i and j. When the agent moved, she stepped on spaces along her path. Inputs were weighted by exponents α and β, respectively.

The rationale for using a multiplicative functional form was to realistically represent the relationship of exploratory behaviour to the memory and distance inputs (an analogue of similar production functions in economy traditionally referred to as the Cobb-Douglas functional form; Cobb & Douglas, 1928). The α and β exponents are output elasticities of memory and distance costs, respectively. These elasticities measure the responsiveness of the agent's exploration pattern to a change in levels of either memory or distance costs used in the optimization of spatial cognition. Consequently, in cases where one of such exponents is 0, and consequently the input value of either M or D is 1, the multiplicative function truly reflects the fact that the agent is solely responding to the complementary input value. In contrast, an alternative additive type function would create biased outputs and give way to unrealistic interpretations at 0 value exponents.

After the exploration of all five objects, the agent returned to the start position and performed the same three consecutive 3-objects navigation tasks as described in Phase 3 of the human experiment (see details in the Procedure section in Chapter 2). The search algorithm in this phase was finding the closest target object of the current 3-objects task. However, to solve these tasks, the agent could only travel on the previously explored paths. If two targets were at equal distance from the agent, she chose randomly between them. Once all the navigation tasks were finished, the run ended.

The α and β weightings of the memory and distance strategies were systematically varied from 0 to 1 with increments of 0.1, so that all combinations of the two spatial strategies were tested. In total, there were 119 individual runs in this parameter sweep ($n = 119$). The agent's initial exploration paths were recorded in each run together with the final navigation task performances. Performance measures were taken both according to the memory and distance efficiencies.

Results

Exploration Patterns

The 119 initial exploration patterns were classified using the algorithm detailed in Chapter 2. Although the first hierarchical clustering (Appendix D) determined an estimate of 59 versus 60 members in two groups, the non-hierarchical validation clustering (K-means) refined the group memberships and put 35 patterns in the first and 84 patterns in the second group.

Individual exploration patterns in each group were collapsed into two meta-patterns and compared to the patterns from the human experiment (Figure 16). Although the actual visual appearance was slightly different in the ABM from that of the human experiment reported in Chapter 2, the main feature of the first cluster (axial group) in both studies was that explorers were using a single route and visited objects in a fixed sequence. Explorations were limited to a less extended spatial area than in the other group. This spatial strategy simulates route-following with a lower demand on the memory system, as only object-to-object associations needed to be learnt.

In contrast, the second cluster (circular group) in both studies included more than a single option to navigate from one object to another. Consequently, it spread out to a larger spatial area than axials. The extended exploration of the circular group simulates the construction a more flexible spatial representation. This spatial strategy uses more than one alternative route between objects and represents a higher memory cost on the cognitive system (see Hartley et al., 2003 for more details on the difference between route-following and wayfinding spatial strategies).

Navigation Performance

A 2 (pattern: axial, circular) x 2 (efficiency: memory, distance) mixed model analysis of variance (ANOVA) was performed on the navigation cost as a dependent variable. The distributions for both the memory, $K(119, N = 119) = .29$, $p < .001$ and distance efficiencies $K(119, N = 119) = .40$, $p < .001$ were different than the normal. As a consequence, non-parametric tests were used for the *post hoc* interaction analysis.

Significant main effects were revealed for exploration pattern, $F(1, 117) = 137.47$, $p < .001$, partial $\eta^2 = .54$ and navigation efficiency, $F(1, 117) = 1564.50$, $p < .001$, partial $\eta^2 = .93$. The Pattern X Efficiency interaction was also statistically significant, $F(1, 117) = 135.38$, $p < .001$, partial $\eta^2 = .54$. The average α (weights for the memory cost: $M_{i,j}$) in the axial group was higher ($M_{axial\ \alpha} = .58$) than in the circular group ($M_{circular\ \alpha} = .34$). This demonstrated that axial exploration patterns emerged when the agent's spatial strategy was more focused on minimizing the memory costs. In contrast, the β (weights for the distance cost: $D_{i,j}$) was higher for the circular explorers ($M_{circular\ \beta} = .65$) than for axial explorers ($M_{axial\ \beta} = .44$). Circular exploration patterns therefore emerged when the agent chose a distance cost minimization strategy.

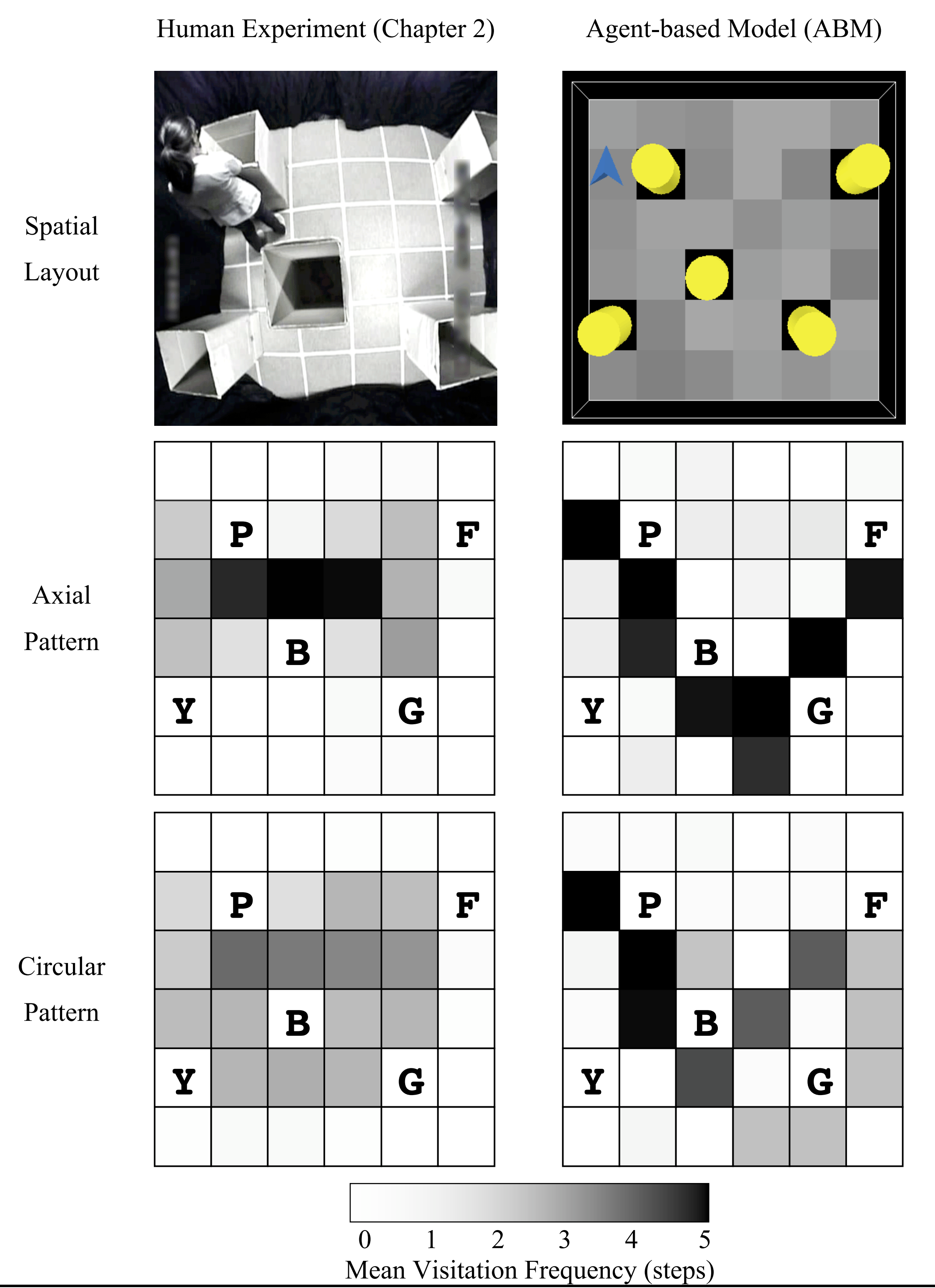


Figure 16. The spatial layout of the physical space in Chapter 2 (top left) and the computational model space in the ABM (top right). In both, axials (middle row) were using a single main route to explore the objects, whereas circular explorers (bottom row) used multiple routes and explored more extended spatial areas. The gray shadings and objects are the same as in Chapter 2.

The significant interaction suggested that axials and circulars optimized their navigation costs differently according to how efficiency was measured (Figure 17). As the parameter weightings indicated, axial explorers were more memory efficient navigators with fewer numbers of squares entered (M_{axial} = 6.10 squares; SD_{axial} = 1.54) than circular explorers ($M_{circular}$ = 7.54 squares; $SD_{circular}$ = 1.42), U = 873.00, W^2 = 4443.00, z = -3.72, p < .001. According to the distance measure, however, the circular explorer group was more efficient in their navigations, as they travelled less overall distances ($M_{circular}$ = 19.46 squares; $SD_{circular}$ = 1.84) than axials (M_{axial} = 27.94 squares; SD_{axial} = 3.79), U = 170.00, W^2 = 800.00, z = -8.98, p < .001. This pattern of results is consistent with the results found in the human participant experiment as can be seen by comparing Figure 17 with Figure 9 in Chapter 2.

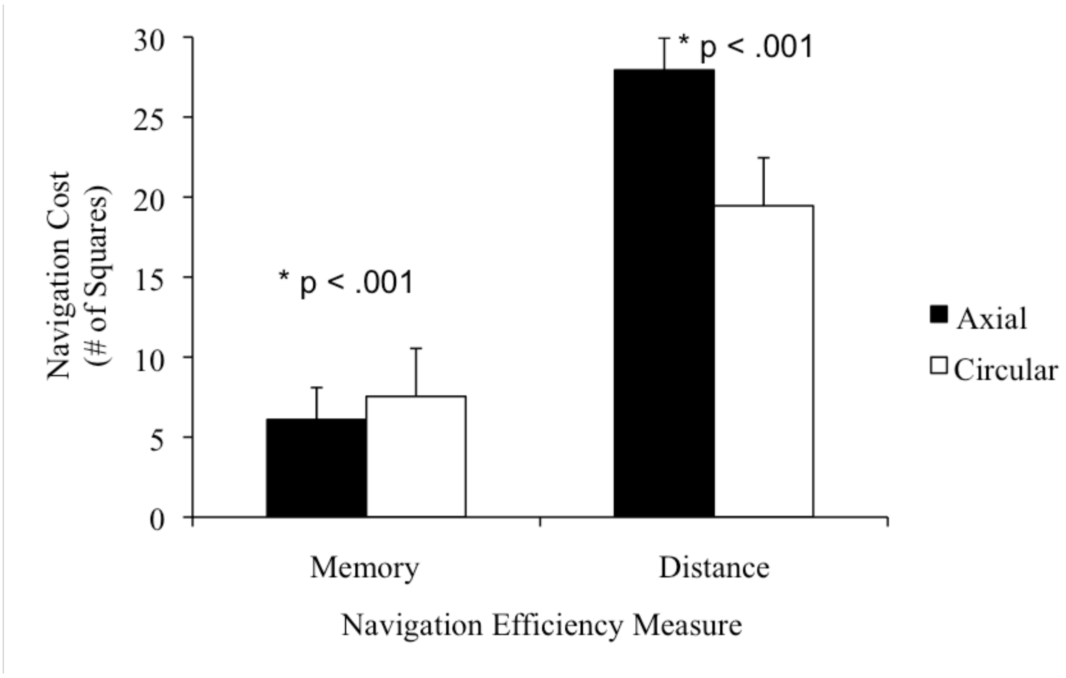


Figure 17. When the agent was exploring on an axial pattern, her subsequent navigation performance was more memory efficient with fewer visited squares. In contrast, circular exploration pattern led to more distance efficient navigation with shorter total distances travelled during the same task than axials.

In the human study, the initial exploration patterns predicted navigation performance (Chapter 2). Further to the presented interaction, the effects of the two spatial strategies in this ABM, parameterised by α and β, is predicted over the navigation efficiencies by a linear regression analysis. This confirmed that α and β were good predictors for navigation steps, as these variables were together accountable for over 62% of the outcome variance, $r^2 = .62$, $b_\alpha(116) = 2.47$, $t(116) = 8.38$, $p < .001$ and $b_\beta(116) = -3.23$, $t(116) = -10.79$, $p < .001$. These results show that as α increases by one unit, the predicted navigation costs increase over two squares. Whereas, a single unit increase in β predicts over three squares shorter navigation.

Discussion

This chapter presented an agent-based model of human spatial strategy optimization. An artificial agent evaluated the different costs of travelling routes to five objects on a two-dimensional square computational model space. The evaluation used a cost function that optimized utilities of two complementary spatial strategies. The memory strategy focused on route familiarity (i.e., already visited paths) and the distance strategy considered travel distances (i.e., minimizing length). Both strategies were augmented in the cost function and associated with parameter weightings (α and β, respectively) in a reciprocal way that reflected on the complementary nature of the two strategies. These strategies were implemented based on the M-D hypothesis supported by experimental findings with human explorers in physical and virtual environments (Chapter 2 - 4).

The results from this model demonstrated that human exploration patterns could be simulated with simple spatial strategies of cost-benefit analysis. The five objects were explored either in an axial or in a circular pattern, determined by a trade-off, whether the agent was optimizing for spatial memory or travel resources. To minimize cognitive costs, the agent followed a single well-learnt familiar route, even if that led to longer overall navigations. In contrast, when the agent optimized for greater distance efficiency, she invested more of her memory resources to develop larger and circular exploration routes. This increased spatial area, simulating a more flexible human spatial representation, allowed the agent to find shorter paths between objects, hence having a more distant efficient navigation performance.

The agent's strategy optimization could provide a plausible functional explanation for human spatial navigation and exploration patterns. These findings are parallel and further explain some of the lessons learned from previous studies examining human exploratory behaviour, where similar trade-offs were found between walking the shortest paths and choosing familiar routes (Gaunet & Thinus-Blanc, 1996; González et al., 2008; Hartley et al., 2003; Helbing et al., 1997).

Chapter Summary

The goal of this chapter was *not* to present a high-fidelity model of human navigation. Rather, it sought to demonstrate that the *memory-distance* hypothesis, formalised as parsimoniously as possible, is *sufficient* to generate spatial exploration patterns that resemble patterns observed in laboratory studies. Human navigation is no doubt more complicated than the highly stylized model employed here. Efforts to solve navigation problems such as the Travelling Salesman Problem have generated entire literatures predicated on mathematically advanced, and computationally cumbersome, solutions to problems which humans seem incredibly well adapted to solving with surprisingly high levels of efficiency (Lawler, Lenstra, Rinooy Khan, & Shymoys, 1985). It has been suggested that humans are able to solve such spatial problems in spite of their cognitive limitations because they dutifully employ simple heuristics, such as the model formalised in this chapter (Chronicle, MacGregor, & Ormerod, 2006; Gigerenzer, 2004; MacGregor, Ormerod, & Chronicle, 2000). The *memory-distance* hypothesis represents a functional abstraction of the heuristics used by human participants in Chapter 2, and it shows promise as a theory capable of usefully predicting human behaviour.

Before drawing a final conclusion based on the experimental and modelling results from the previous chapters, a diversion from the theoretical line of research established up to this point will be made in Chapter 6. The next chapter presents a real-world application of the previously discussed theoretical navigation principles. The domain for this investigation is the archetypical digital information space, the web (Benyon, 2005). More specifically, a practical problem in *e-learning* will be investigated, which often involves exploration of hyperlinked webpages, similar to the exploration of space in the real world. The question in Chapter 6 is what are the gains and losses of allowing the learners to control their explorations in an abstract information space? In other words, how spatial strategy optimization takes place during e-learning?

As demonstrated in previous chapters, initial paths of exploration taken in any environment (be it a physical, virtual, or any other type) will not only guide the discoveries of what the environment contains, but also formulate the underlying cognitive organising principles. The suggested route in an art gallery frequently presents artworks that are either chronological or conceptually tied together.

Deviating from this and taking a route of our own might be either confusing or insightful. The structure of the information and the control that the learners have in exploring it play a major role in determining spatial representations and learning. In abstract spaces (i.e., virtual or informational spaces) these possibilities and degrees of freedom in navigation are less constrained than in the physical world, and thus, can be colossal. The practical question that arises is what are the gains and losses of allowing the e-learners to control their explorations? To investigate this, Chapter 6 presents three e-learning layouts that differed in their navigational possibilities and structure, but all contained the same learning material. The results will be described and interpreted with specific attention on how navigational control can either enhance or hinder efficiency.

Chapter 6: Giving the e-learners control of navigation: Navigational gains and cognitive losses

Previous chapters of this thesis presented four empirical studies of spatial strategies in different laboratory controlled environments either in physical or abstract spaces. In this sixth chapter the aim is to consolidate the theoretical findings so far and apply them in an ecologically valid, real world problem within the domain of technology enhanced learning. Technology enhanced learning takes place when various technologies (e.g., computer, mobile, gaming, informal) are used to enhance the acquisition, memory and impact of human learning (Dror, 2008). The most common form of technology enhanced learning is e-learning, which itself has gone through many phases of development before it became the most rapidly growing and influential medium of education and training worldwide (Downes, 2005; Nagy, 2006). Instructional designers, developers, usability experts and other training professionals team up to build e-learning environments that provide efficient and cost effective learning solutions. Finding the optimal e-learning spatial layout for each task that lead to the best learning outcome is amongst their prior concerns. This provides an opportunity to draw comparisons with the research outlined in this thesis. For instance, Chapter 3 with the Yellow Brick Road study demonstrated that certain forced exploration layouts could affect navigation performances. Following up on those findings, this study will look at how learning through different e-learning layouts affects memory.

Information space in an e-learning environment encompasses a set of distributed pages across a hyperlinked website (Benyon, 2006). Following graph theory notations, an individual page is referred to as a node and a link between two nodes as an edge (see Figure 5). A single node, however, contains only a fraction of the overall information available within the environment and to acquire comprehensive knowledge the learner has to navigate through the nodes via the available edges. The act of visiting other nodes includes a navigational travel cost that is analogous to physical steps taken in the real world. The learner invests equal travel cost for each node visited; however, the amount of information acquired (cognitive gain) might not be the same at all nodes. Previously non-visited nodes, for example, are more likely to contain novel information that the learner could process.

On the other hand, a better understanding of the material might require repeated visits to the same node, which could increase the travel costs for the same cognitive benefit. When navigating through an information space the learner not only acquires content knowledge but also learns about the spatial layout of the learning environment. This approach of user navigation is based on the theory of information foraging (Pirolli & Card, 1999). The theory assumes that learners continuously re-evaluate their expected utilities by cost-benefit analyses. More recent explanations argue that most users, however, adopt only a limited number of strategies when navigating through an e-learning environment, even if their comprehension of the material is poor (Miura, Fujihara, & Yamashita, 2006; Spink & Cole, 2006). Learning in a hyperlinked space therefore could either enhance or hinder efficiency depending on a variety of factors, including the cognitive mechanisms that are not yet fully understood.

Navigation in the informational space is similar to navigation in real space in a sense that it is spatially determined (Boechler, 2001). The routes in a hierarchically and semantically structured informational space are the node visit sequences. The users – at each node – have to allocate their cognitive and energy resources on (i) navigational tasks: planning and executing routes; (ii) informational tasks: learning about the content; and (iii) task management: coordinating informational and navigational task (H. Kim & Hirtle, 1995). A classic real world example is the art museum problem (originally posed by Foss, 1989). This navigational problem relates to the information retrieval difficulties when visiting a huge art museum without detailed encoding of some of the specific art works or without conceptually focusing on a particular aspect of the whole exhibition (e.g., missing the “positive impressions of negative spaces” at the *Embankment* exhibition, see Preface on page 14). In hypertext systems with high cognitive navigational costs, the demands might exceed the user’s task management capacities, who could as a result become disoriented and ultimately get lost (Foss, 1989). Consequently, the applied spatial strategies of how people deal with the distributed information in a hypertext environment will adapt to the interaction between the informational and navigational demands (Benyon, 2006; Herder & Juvina, 2004; H. Kim & Hirtle, 1995; Pirolli, 2005).

Some e-learning layouts are designed to determine the navigational behaviour by varying the amount of control the users can have. Control in the context is defined as the ability of the user to individually determine the order of appearance of the learning material (Eveland & Dunwoody, 2001; Southwell, Anghelcev, Himelboim, & Jones, 2007). The effects of allowing control to the learners in information spaces have been studied in relation to the level of expertise (Patel, Drury, & Shalin, 1998), hypertext structures (McDonald & Stevenson, 1996), learning performance (Southwell et al., 2007) and other individual differences (Sas, 2004). The findings from previous studies are not conclusive. On the one hand, higher control tends to be perceived as an enhancing factor if the user is experienced in the applied information technology (Southwell et al., 2007). On the other hand, less experienced users could become overwhelmed by the high degrees of options that control provides them; hence, their performance deteriorates. This negative effect is believed to originate in a memory encoding inhibition by overly complex informational demands (Southwell & Lee, 2004). However, previous literature on user control in e-learning lacks quantitative investigation into the interaction between the navigational and informational tasks.

The present experiment was designed with the view to amend the gap in the literature and investigated how the different levels of navigation control in e-learning layouts affected actual navigation behaviour. As a novel aspect to previous research, both short and long term memory were assessed. Three e-learning layouts were created (axial, star, circular) with increasing level of control given to the participants. The layouts differed from each other only in their edge structure (travel demand), but not in their information content (cognitive demand). The axial layout offered sequential routes (high travel demand and low cognitive demand), whereas the star layout was moderate and the circular had complex route structures (low or moderate travel demand and high cognitive demands). The reason for including a star layout was to reflect on the very common ‘search engine’-type situations, where a central results page anchors further navigations. Learning in the axial layout with less control was expected to result in higher navigation activity (i.e., more node visits) and consequently more vivid immediate memory of the content. However, the higher travel demand is expected to result in less integrated knowledge of the relationships between the topics. In other words, short term advantage of higher exposure to the learning material is expected to attenuate with time. On the other hand, more navigationally complex environments should have less effective immediate learning outcomes, due to the increased informational demand. Nevertheless, complexity in the layout should enhance information retrieval and long term recall performance.

Method

Participants

One hundred and seven students from the University of Southampton volunteered to participate in the present study (n = 107). Participants were recruited from an optional psychology course and they received course credits for their participation. The experiment complied with the requirements of the School of Psychology, University of Southampton's Ethics Board. All the participants gave informed consent and they were debriefed with the aims of this research after completion of the experiment.

Apparatus

The study had two parts: computer-based e-learning and paper-based tasks. The computer-based task consisted of an e-learning session, which was purposely designed and programmed for the present study. The hyperlinked pages and the algorithms employed to record user behaviour were programmed using the HTML, PHP, AJAX and JavaScript programming languages and the MySQL relational database management system. The experiment took place in multiple consecutive group sessions in a lecture theatre with 60 standard PC computers. The material was presented on 15-inch monitors with standardized screen resolution. In this mode no scrolling was required to read the learning content. All computers were running Microsoft Internet Explorer 6.0 in full screen mode.

For the e-learning task, the material involved eight topics of human memory that were related to the cognitive mechanisms of remembering and forgetting. Each topic was explained on a single page (node). All three e-learning layouts presented the material in a framed box that occupied the top two third of the screen. The font sizes and styles, colours and frames remained constant throughout all conditions. A link to terminate the study at any time was present at the bottom of the screen (Appendix E).

Although the content of the e-learning material was the same for all participants, the design of the three layouts was different in their hyperlink navigation options (edge structure). The first layout (axial) presented the nodes sequentially (Figure 18). Control of navigation was limited to two arrows positioned at the left and right bottom of the screen. From each node, participants could only move to the subsequent node, or one back to the previous node. This arrangement did not allow alternation from a set order of navigation and there was no overview of how the nodes are linked to each other. The only indicator was the number of the current node out of the total number of nodes shown between the two arrows. In order to avoid order effects, the page sequences varied randomly across participants.

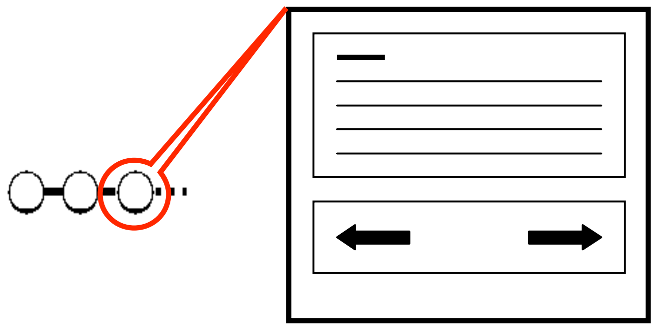


Figure 18. Axial layout (left) and a schematic view of a single webpage (right). Participants had no overview and they were offered limited control of their navigations with only the back and the forward arrow buttons present.

The second layout (star) included and started with a central index page, where the names of all the eight nodes were listed along a circle (Figure 19). The order of nodes presented on the index page was randomised across participants. Any nodes could only be chosen from the index page. Once a particular node was visited, the participants always had to navigate back to the index page in order to choose the next node. Therefore, this layout partially restricted control by enabling free navigation but only from an index page (‘search engine’ type layout).

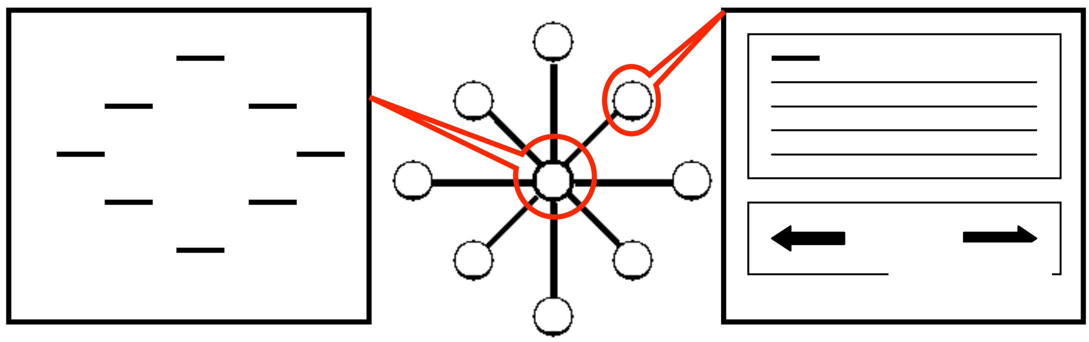


Figure 19. Central index page (left) of the star layout (middle) and a schematic view of a single webpage (right). Participants could navigate to webpages in any sequence on the index page. However, their navigation control was partially restricted, as they always had to return to this index page once they have finished reading a page.

In the third layout (circular), all nodes were present at all times during learning without a central page or other browsing limitations (Figure 20). The eight nodes were listed along a circle at the bottom of the screen, while the currently selected content was shown above. These settings granted total control to the participants as they could freely and directly navigate and visit any page from any other page.

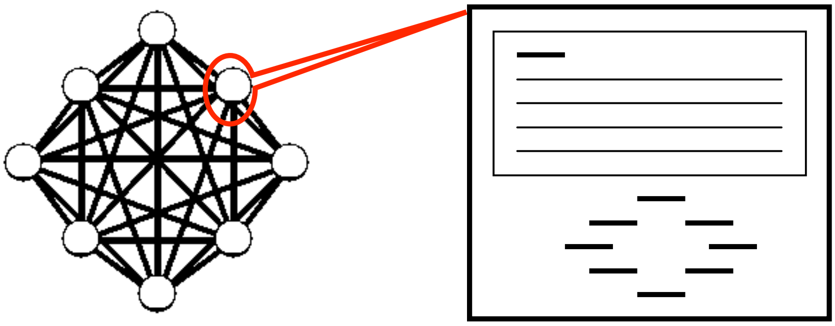


Figure 20. Circular layout (left) and a schematic view of a single website (right). All 8 nodes were available at all times of the learning, while the current content was shown on the top part of the screen. This layout provided full navigational control over the e-learning, as the participant could freely decide the page visitation sequence.

Once the participants finished the computer-based task, they were immediately administered with a paper-based test that assessed their memory performances. They were asked to write a short essay about each of the 8 newly learnt topics and to sketch a map of how they imagined the semantic connections between these concepts.

Procedure

The experiment began with an on-screen consent form shown to the participant. They were asked to read it carefully and with their agreement they continue to the instructions page. After entering basic demographic information (e.g., age and gender), participants began the actual experiment and were directed to the first page of one of the three e-learning layouts (axial, star or circular). Participants were automatically assigned to one of the conditions by the server in order to keep the groups equal in their size. The computer recorded all exploration activity within and between nodes. After completing the computer-based task, participants completed the paper-based tasks. There was no time limit for the participants to finish the tasks; however, the whole experiment did not take longer than 60 minutes.

Two weeks after the experiment, the participants were re-assessed with the same paper-based tasks (8 short essays and sketch maps) to test for long-term memory retention without e-learning. The procedure of registering the paper-based tasks was identical to the first time. Because the study was voluntary, this time only 77 out of the original 107 participants were present at the time of testing.

Results

The parametric assumption of normal distribution was not met within the measured dependent variables, therefore group differences between the three layouts (axial, star, circular) were analysed with non-parametric Mann-Whitney tests. Additionally, only those node visits that took longer than 3 sec were included, to avoid potential bias by those nodes that were rapidly flipped through the learning.

Navigation Behaviour and Complexity

Participants spent equal amount of time viewing the nodes, $H(2) = 3.41$, $p = .18$. However, the number of nodes visited was significantly different, $H(2) = 10.57$, $p < .01$. Three separate post-hoc Mann-Whitney U tests revealed that the axial group visited significantly more nodes than the star group, U = 404.00, $W^2 = 1034.00$, $z = -3.00$, $p < .01$. Axial group also had more node visits than the circular group, U = 436.50, $W^2 = 1031.50$, $z = -2.42$, $p < .05$. There was no difference between the star and circular groups, U = 523.50, $W^2 = 1153.50$, $z = -.89$, $p = .37$. The group means and standard deviations are presented in Table 2.

Further measures of navigation complexity were calculated from page visitation sequences for each participant and for each node separately (Rauterberg, 1992). Participants in the three e-learning layouts followed significantly different number of links from each node (fan degree), $H(2) = 25.27$, $p < .001$. Both the axial and star groups had more links from each individual node than the circular group. In addition, the circular group returned less regularly to previously explored nodes than the axial or the star groups (path density), $H(2) = 17.23$, $p < .001$.

Table 2
Means and Standard Deviations of Navigation Behaviour and Complexity Measures in the Three E-Learning Layouts

	e-Learning Layout		
	Axial	Star	Circular
N	38	35	34
Time per node			
Mean (ms)	67.56	69.90	67.23
SD	60.66	33.84	35.63
# of Nodes			
Mean (node)	16.58	10.40	10.88
SD	8.30	3.64	4.41
Fan Degree			
Mean (edge)	2.07	2.39	1.38
SD	1.03	.77	.52
Path Density			
Mean (return rate)	.29	.30	.20
SD	.15	.10	.07

Memory Recall

Double-blind research assistants, who were not informed of the aims of the study, scored the eight short essays of each participant at both time points (immediately after e-learning & two-weeks later). A maximum of three points per essay was given if all necessary and correct topics (node) were recalled. Two points were awarded, if the essay was correct but incomplete. Zero point was given if the essay was incorrect or missing. Not every participant handled in essays. There were 102 essays collected immediately after e-learning and 77 essays two-weeks later. See detailed group means and standard deviations for the memory recall tasks in Table 3.

Table 3
Means and Standard Deviations of Memory Recall Scores in the Three E-Learning Layouts

	e-Learning Layout		
	Axial	Star	Circular
Immediately After E-Learning (T0)			
N	35	35	32
Recall score	16.91	14.80	13.88
SD	4.56	5.50	5.10
Two-weeks After E-Learning (T1)			
N	26	28	23
Recall score	8.85	7.71	7.57
SD	3.34	3.73	3.70
Decay (T0-T1)	8.06	7.09	6.31

The results showed a significant difference between the recall scores immediately after the e-learning session, $H(2) = 6.75$, $p < .05$. Post-hoc tests revealed that the axial group remembered the most topics correctly, while the circular group performed the worst, U = 356.50, $W^2 = 884.50$, $z = -2.56$, $p < .05$. There was no difference between either the axial-star, U = 464.00, $W^2 = 1094.00$, $z = -1.75$, $p = .08$ nor the circular-star groups, U = 504.50, $W^2 = 1032.50$, $z = -.70$, $p = .49$.

The memory recall difference between the three groups disappeared when the participants were re-assessed two weeks later with the same short essays, $H(2) = 3.53$, $p = .17$. The grand mean recall score of the groups on the second assessment was 8.05 nodes compared to 15.24 nodes immediately after learning.

More importantly, however, the difference in scores for the first and second tests (decay) was less for participants in the circular group than in the axial group, U = 186.00, $W^2 = 462.00$, $p < .05$. The decay in the star group did not differ from either of the other two groups (U = 323.00, W^2 = 729.00, z = -.71, p = .48 and U = 246.00, W^2 = 522.00, z = -1.45, p = .15, in comparison with the axial and the circular groups respectively).

Sketch Maps

As part of the paper-based assessments participants were asked to sketch a map of how they imagined the semantic connections between the learnt concepts. Out of the 107 participants, only 61 (56%) responded to this question immediately after learning and only 35 (32%) after the two-week delay. To analyse these maps the drawn nodes showing a learnt concept were counted. Drawn edges were also recorded, when any two drawn nodes were connected with a line. See Table 4 for the descriptive statistics of the sketch maps.

Table 4
Means and Standard Deviations of Drawn Nodes and Edges on the Sketch Maps in the Three E-Learning Layouts

	e-Learning Layout		
	Axial	Star	Circular
Immediately After e-Learning (T0)			
N	21	21	19
# of Drawn Nodes	7.81	4.29	6.42
SD	2.70	3.13	2.32
# of Drawn Edges	5.95	3.38	4.21
SD	2.77	3.32	3.58
two-weeks After e-Learning (T1)			
N	10	13	12
# of Drawn Nodes	4.80	2.15	5.17
SD	3.08	2.27	3.33
# of Drawn Edges	4.00	2.46	2.25
SD	3.06	3.41	3.28

There was a significant difference in the average number of drawn nodes immediately after learning, $H(2) = 12.45$, $p < .01$, and it was due to the low star group compared to the higher circulars, U = 115.00, $W^2 = 346.00$, $z = -2.30$, $p < .05$ and higher axial group scores, U = 91.05, $W^2 = 322.50$, $z = -3.26$, $p < .01$. Axials and circulars, however, did not differ from each other, U = 142.00, $W^2 = 332.00$, $z = -1.58$, $p = .12$. Similarly, the number of edges were significantly different between the three groups, $H(2) = 7.08$, $p < .05$. In this case the star and the circular groups did not differ, U = 174.00, $W^2 = 405.00$, $z = -.70$, $p = .50$, whereas the other two comparisons were significant (U = 125.00, $W^2 = 315.00$, $z = -2.03$, $p < .05$ and U = 125.00, $W^2 = 356.00$, $z = -2.42$, $p < .05$, for the axial-circular and axial-star respectively).

Two weeks later, when the participants redrew their sketch maps, the same pattern of group differences was observed for the number of drawn nodes, $H(2) = 6.89$, $p < .05$. On the other hand, this time the number of drawn edges was equal in all three conditions, $H(2) = 3.32$, $p = .19$.

Discussion

This study investigated how different e-learning design layouts affected navigation behaviour and memory recall with a specific focus on navigation control. The three layouts provided low, moderate or high degrees of freedom in terms of navigational control given to the participants. It was found that while the participants spent equal amount of time learning the material in all the three layouts, the axial group visited more nodes during this time than the star and the circular groups. This suggests that linearly structured, more restricted (axial-type) e-learning settings force the users to intensify their navigation activity when learning a new e-learning module.

There can be several reasons for this increased navigation travel cost in the axial condition. The lack of an overview in the axial structure, for instance, could hinder planning of the learning routes and, thus, increase returns to previously visited nodes. In contrast, learning in those layouts where all nodes are more readily available from the first encounter a simple, effortless and better-planned navigation strategy should be sufficient to visit all the pages. Although the circular group seemed to apply such simple navigation strategy, the star group – with site overview on the index page only – was more similar to the axial group with rather complex navigation behaviour as shown by the graph theory measures (fan degree and path density). Consequently, the lack of overview is unlikely to be the primary cause for the increased navigation activity.

Alternatively, further information foraging strategies could exist in e-learning environments. Participants in axial hyperlink structures cannot get an instant understanding of how the nodes are related to each other. To compensate for this information deficit, they increase their navigation travel expenses; hence, they visit more nodes. E-learning structures with limited user control (e.g., axial and star) force the participants to use shorter planned navigation sequences and more frequent returns to previously visited pages. In environments with more user control (e.g., circular), participants are not necessitated to revisit nodes more than once, as they can remember and monitor their planned routes throughout the whole session. In fact, this is exactly what was found in the present experiment. This finding supports the claim that hyperlink structure influences navigation behaviour via the amount of control given to the participants.

Navigation behaviour analysis in itself is not very informative and has to be accompanied with memory recall measures in order to evaluate learning efficiencies. The results in this study showed that the increased navigation activity in the axial group was associated with the best short-term memory performance, whereas the circular group performed the worst and the star pattern in between. This finding reinforces previous findings of web design studies that axial-like structures are more efficient than hierarchical or more complex non-axial ones (e.g., McDonald & Stevenson, 1996; Southwell & Lee, 2004). Nevertheless, in all these studies performance has only been measured immediately after learning, but not weeks following the e-learning session.

In the present study, long-term memory performances were also assessed and it was found that the advantage of the axial layout disappeared when participants were re-examined two weeks after their original e-learning session. In effect, there was a significantly greater drop in memory recall in the axial group, whereas the circular and star groups performed more steadily over time. This suggests that although e-learning layouts with higher navigation freedom (circular-type) have smaller immediate learning effectiveness, the learnt information consolidates more effectively than in restricted control layouts.

Long-term memory processing is both semantic and relational – in other words, providing learning material in a coherent structure can be used as a tool for memory (Baddeley, 1997). Participants in the circular group were not only spending their cognitive resources on serially accessing, learning and remembering the e-content but they were also planning, executing and monitoring the sequence of their own exploration. This extra navigational strategy component led to a decreased immediate performance, but also to a lower rate of memory decay over time. In contrast, the axial group could focus all their cognitive capacity in memorizing the nodes right after learning without the need to plan further steps. Although this might increase subsequent efficiency, but without a deeper cognitive processing into a relational memory structure, the topics could more easily be forgotten. This interpretation was further tested with analysing the sketch map drawings of the participants, whereby they graphically represented the relations between the newly acquired topics.

Without an attempt to analyse the sketch maps of the participants abundantly, only the number of drawn nodes and their connecting edges were recorded. These measures could provide only a rough estimate of how the participants mentally represented the newly learnt topics and their semantic relations to each other (for an overview of such mental imagery tasks see Kosslyn, 1994). The task was found to be either relatively difficult or unclear as only 61% and 32% of the participants returned such a sketch map (immediately after learning and two weeks after, respectively). However, there were an equal number of drawings from participants initially assigned to the three layouts, which means that the completion of the task did not depend on the learning structures.

The second sketch map drawing task confirmed the previously discussed finding that the conceptual links between the nodes faded more easily with time in the axial condition than in the more complex star or circular ones. It also showed that forgetting targeted the remembered edges, but not the number of independent nodes. More freedom in navigation control (i.e., circular layout) given to the participants ensured that the learnt information was remembered better by integrating it into a relational memory system.

Chapter Summary

The study in this chapter investigated navigation behaviour, user control and memory performances in three different e-learning layouts. The experiment provided good evidence of a dissociation between two types of information foraging demands: an informational demand (how much content will be remembered) and a navigational demand (what route will be taken). This finding is analogous and provides a practical application to the *memory-distance hypothesis* discussed throughout the previous chapters of the thesis. The data confirmed that as hyperlink complexity and, thus, navigational control became more cognitively demanding, short term memory performances decreased. It was harder to remember all the topics correctly immediately after learning if more than one route was available to navigate through the material. Cognitive resources were divided in these cases between the navigational task and the informational task. The benefit of higher degrees of freedom in user control was the more integrated knowledge representation and consequently less forgetting in the long term. Limited user control, on the other hand, resulted in greater navigation activity and better performance in the subsequent memory task. This advantage disappeared, however, two weeks after the e-learning session, suggesting that freedom to navigate within the material in hyperlinked environments is required for long term, relational learning.

In the final chapter, the findings about spatial strategy optimizations reported in this thesis will be summarised, and then discussed in terms of their theoretical and practical relevance to spatial cognition research. Following a reiteration of the purpose of the thesis, the main findings will be put into a coherent theoretical context. The chapter will conclude with a discussion of the impact of the current thesis, and suggestions for future work.

Chapter 7: General Discussion

Purpose of Thesis

This purpose of this thesis was to describe patterns of human exploration behaviour and understand the related spatial strategies of cognitive and behavioural resource allocation under different environmental constraints. The basic underlying assumption throughout the thesis was that human cognition seeks an optimal interaction between the individual and his or her environment (Anderson, 1991). To control and explore this interaction experimentally, a square-shaped spatial layout was designed containing five target objects on fixed locations. This layout enabled to examine the factors affecting spatial resource allocation through empirical studies in physical (Chapter 2-3) and equivalent abstract spaces (Chapter 4-5). Navigation performances following an unconstrained free physical exploration (Chapter 2) were compared to exploration on forced physical routes (Chapter 3), in an effortless desktop-based virtual space (Chapter 4). In Chapter 5, a computer simulation was used to formalize the cognitive and behavioural optimization mechanisms of spatial strategies. In addition, Chapter 6 investigated the practical implications of these findings for e-learning instructional design.

Three main research questions were raised as the focus of this thesis: (1) How do people allocate their cognitive and behavioural resources when interacting with their spatial environment? (2) How do spatial strategies predict navigational performance and efficiency? (3) What is the role of the environment in spatial strategy selection?

The main hypothesis was that human spatial cognition is optimized by heuristic spatial strategies that function as trade-offs between the cognitive memory costs of route-planning and the behavioural costs of travelling distances. This was coined as the *memory-distance* (M-D) hypothesis. Further to the M-D hypothesis, exploration pattern identification, spatial strategy optimization, efficiency trade-offs, environmental biases and navigational control were investigated. The following section provides a systematic summary and overview of the empirical findings of the thesis.

Summary of Findings

Exploration Pattern Identification

This thesis identified basic patterns of spatial exploration. Many patterns emerge continuously and it is one of the great tasks of science to identify the *meaningful* ones that capture regularities and help understand how mind, brain, and behaviour are related (Kelso, 1995). The spatial patterns discussed in this thesis are aggregate representations of the participants' initial exploration routes. They are the 'behavioural fingerprints' of spatial strategies. Chapter 2 described a new methodology developed in this thesis that clustered and classified individual exploration patterns into groups based on regularities of the route maps. The classification process included a two-step process. First, a hierarchical cluster analysis indicated a range of solutions for the number of cluster groups. This was followed by a non-hierarchical cluster analysis to validate the group memberships with a 99% confidence rate.

Consistently throughout this thesis, two main patterns of spatial exploration were found (Figure 21). Participants explored the space either in an *axial* or a *circular* pattern. Axial explorers used a single route to visit all target objects and followed a fixed sequence of learnt cues when they were asked to revisit the objects during the navigation tasks. This exploration indicated a cognitively economical spatial strategy as the axial pattern did not require a complex survey-type representation and the task could be solved with route-following (Hartley et al., 2003). In contrast, circular explorers searched the spaces with multiple routes and acquired extended spatial knowledge. The more flexible survey representation allowed these participants to plan alternative routes between target objects and depending on the environment it led to a more efficient navigation performance.

The similarity in pattern shapes across experiments and spaces was accompanied with a consistent 1:3 ratio of participants being identified as axial or circular explorers respectively. A preferential bias towards any particular exploration type was not an expected finding. Although the issue was not addressed directly in the thesis, the results from the YBR study (Chapter 3) suggest that the spatial configuration of the objects, rather than individual differences, have a greater contribution to how people interact with their spatial environments.

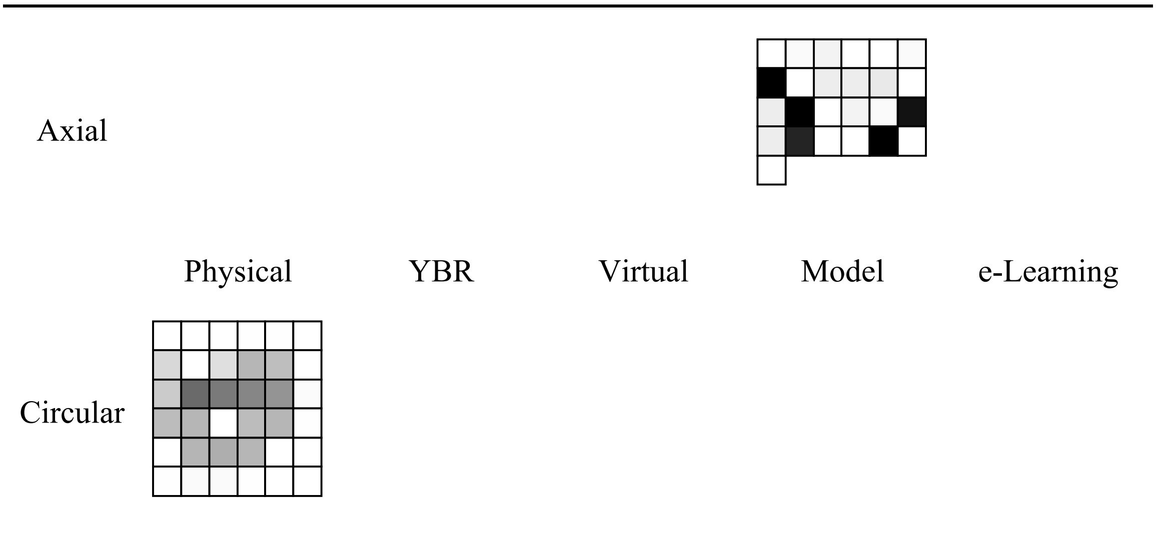


Figure 21. The axial and circular spatial exploration patterns in five spaces. Participants in all studies explored either on a single main route (axial) or on multiple extended routes (circular). The order of the five spaces on the figure corresponds to the chapters of this thesis from Chapter 2 to 6. Note that the initial spatial layout was originally rotated by 90-degrees in the YBR study (Chapter 3) and the webpage links were pre-designed in the e-learning study (Chapter 6). Also note that objects are not shown.

The baseline spatial layout used in the thesis could have induced a more circular-type exploration. However, without further studies it is difficult to answer why more people explored initially as circulars than as axials. Nevertheless, the presence of a consistent ratio of participants in the two patterns provides further evidence that these exploration patterns reflect a meaningful underlying function of spatial behaviour and cognition, details of which need to be examined in future studies. This thesis reveals these patterns using the novel clustering methodology. The contributing factors that cause people to prefer one strategy over the other is important, but beyond the scope of this thesis.

It is important to emphasise that it is not the actual shape or number of the identified spatial patterns that are important, but their underlying functional roles. The shape of an exploration pattern is highly dependent on the spatial layout and it is expected to change the outcome of the learning process in other landmark arrangements or alternative spatial arrays (Esber et al., 2005). Therefore the focus of the reported studies in this thesis was to find cognitively plausible explanations of why such spatial exploration patterns emerge and how they affect navigation behaviour.

The classification method of the exploration patterns in this thesis represents a novel approach in analyzing human spatial behaviour. Previous studies often described recurring visitation sequences either quantitatively (e.g., González et al., 2008) or qualitatively (e.g., Tellevik, 1992). However, no meaningful explanations were provided why individuals navigate the way they do (Thinus-Blanc & Gaunet, 1997). The pattern clusters in this thesis go beyond the structural characterization of visually similar behaviours by associating the observed travel routes with underlying spatial strategies. When these initial exploration pattern groups were used as independent variables in comparing performance levels in subsequent navigation tasks, the results confirmed that they had considerable effects on how participants represented and interacted with their spatial environment.

Spatial Strategy Optimization

Spatial strategies were defined in this thesis as heuristics that allocate available cognitive and behavioural resources for solving spatial navigation tasks. The definition assumes that humans are driven to achieve a locally optimal level of adaptation to the demands of their environment via interactive behaviours (Anderson, 1991; Makány, 2006). In spatial cognition, the demands are split between the cognitive effort of acquiring, remembering and planning a route for wayfinding and the behavioural effort of travelling actual distance in space for locomotion (Chen & Stanney, 1999; Freundschuh, 2004). Allocations of these resources take place in a series of cost/benefit trade-offs that aim to maximize the difference between the expected gains and related expenses of goal-directed spatial behaviours (Gray & Boehm-Davis, 2000; Gray et al., 2006). As a consequence, spatial strategies may result in many locally good route solutions, and although they could be close to the shortest one, they are often very different both from this distance-optimum and from each other (Charter & Oaksford, 1999). This suggests that there are other measures of spatial optimality than just finding the shortest distance. The significant interaction in Chapter 2 of this thesis provides a good illustration for this as the circular explorers were distance efficient navigators, but the axial explorers rather optimized their navigation around a single and easy to remember route even if that later entailed longer overall travel routes. The spatial strategy behind the circular exploration pattern suggests a preference for initially higher cognitive costs that could be traded in for distance efficiency, whereas the trade-off was in the opposite direction for the axial exploration pattern group.

Spatial strategies are analogous to heuristic strategies in game theory, a set of rules that are capable of finding optimal solutions to win a game or to reach a goal (von Neumann & Morgenstern, 1947). These rules are not clear and well defined algorithmic steps that always lead to the same predictable and deterministic outcome, but rather statistical probabilities that adapt to the existing circumstances. Spatial strategies, in particular, are dynamic adaptations to the continuously changing interactions between the individual and its spatial environment. None of the studies in this thesis claimed to describe a globally ‘optimal’ spatial strategy that always guaranteed the best performance. For example, spending less cognitive effort on exploring and learning alternative routes and following a single route in a virtual space (Chapter 4) did not lead to longer navigation distances, as it was the case in the equivalent physical space (Chapter 2). The heuristic of travel distance optimization (distance strategy) is adapted to the required costs of the task environment. The travel cost was minimal in the virtual space where only the joystick was pushed back and forth while the participants were sitting in front of a computer monitor. Due to this low cost of locomotion, they chose to travel virtually longer distances (with minimal to no-cost) than to mentally recalculate a route. This is an illustration of the principle that spatial strategies optimize navigation according to a fine balance between available cognitive and behavioural resources and that balance is highly sensitive to the task environment.

Strategies have a dual nature by reflecting both structural communalities and programmatic patterns of human cognition (Gordon, 2004). In other words, they include an intentional plan that can manifest in recurring patterns of behaviour. To understand the strategic intention of a goal-directed behaviour (for example frequent visits to the library or exploring objects in the experimental room) the interaction between the environment (location of the library/objects) and the recurring behaviour (borrowing books/walking around the room) need to be considered jointly. If the behaviour is repeated in similar forms, the analysis of the recurring features could provide an insight into the meaning of the behaviour itself. In the first example, if the borrowed books are all about the paintings of Wassily Kandinsky, the borrower is likely to be interested in early modern abstract art. Similarly, the analysis of exploration patterns indicates if the explorer is memorizing the objects on a single route, which suggests that the memory costs are considered more important for the spatial optimization process than the distance costs and that a route-following navigation strategy was selected. However, in order to validate such assumptions, the computational findings from the agent-based model (Chapter 5) are needed. In the model, a single artificial agent was exploring and navigating the equivalent computational space as humans in the physical room. In a total of 119 iterations, the agent swept through combinations of memory and distance parameter optimizations. This model-based testing of the M-D hypothesis showed that spatial strategies provide a plausible functional explanation for human navigation performances and exploration behaviours. The same exploration patterns and optimization trade-offs were found between the cognitive (choosing familiar single route) and behavioural (travelling the shortest distances) parameters in the model compared to the baseline study. The behavioural experiments and accompanying model therefore support the M-D hypothesis. Furthermore the test results showed that as a theory, the M-D hypothesis is capable of predicting human spatial behaviour and performance levels.

Efficiency Trade-offs

The second research question in this thesis was how spatial strategies predict navigational performance and efficiency. To answer this, first the notion of optimality in human cognition was examined. Human cognition is considered a locally optimal response to the various demands of the task environment (Anderson, 1991). We allocate limited resources selectively in order to satisfice with our behaviour. This means that we do the best we can (local optima) but not always the best possible (global optima) (Lea, 2006). This non-maximizing local optimization is the consequence of the narrow bounds of human rationality (Mérő & Mészáros, 1990; Simon, 1955, 1979). The optimization is happening through continuous trade-offs in the process of cognitive and behavioural resource allocations (Gray & Boehm-Davis, 2000; Gray et al., 2006). The balance between these resources determines efficiency. I have argued throughout this thesis that the evaluation of task performance is conceptually difficult and multiple efficiency criteria should be applied.

Within the domain of spatial cognition, the need for separate efficiency measurements was recognised by Ruddle and Lessels (2006a). They proposed three levels of metrics to evaluate wayfinding: task performance, physical behaviour and cognitive rationale (Figure 22). Each level has various task measurements, such as target finding time, travelling distance, rotations, heading errors or think aloud and other qualitative techniques. Although this approach presents a very comprehensive description of the different aspects of wayfinding, it lacks a functional explanation of how the levels are connected and inter-related to one another. In addition, the hierarchical levels implicitly give greater importance to the cognitive resources during the allocation process, which is against the idea of local optimality via cost-benefit trade-offs (Gray et al., 2006). Interestingly, the results from Chapter 4 could provide an explanation to this bias towards cognitive processing in the Ruddle and Lessels study. Based on the findings in this thesis, participants change their initial spatial strategies and favour cognitive optimizations over being distance efficient due to the minimal travel costs in an effortless virtual space. However, this is a bias in the specific environmental circumstances (see also the next section of this General Discussion) and does not reflect a functional role of spatial cognition.

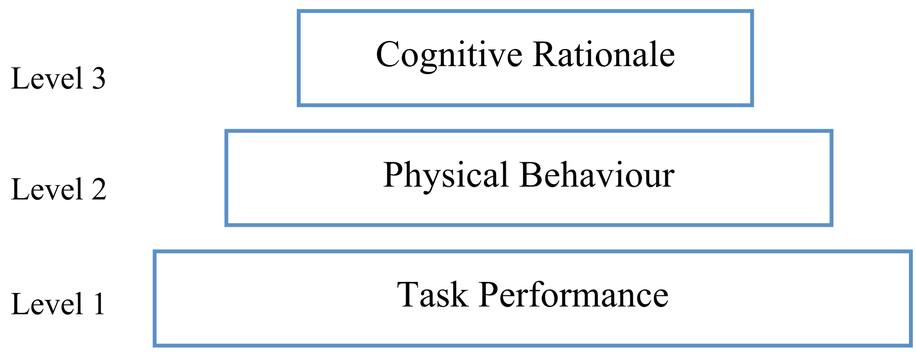


Figure 22. Three levels of metrics to evaluate wayfinding according to Ruddle and Lessels (2006a). These metrics are hierarchical and assume higher order functionality to the cognitive rationale element.

The thesis also incorporated multiple efficiency criteria by evaluating navigation performances according to two different measures of optimality. The measure of memory efficiency quantified the size of the space that was used during the navigation task, while the measure of distance efficiency expressed the total travelled route lengths. Each of these measures reflected on the cost allocations of either the cognitive or the behavioural resources. The comparison of these measures between the exploration pattern groups provided a meaningful insight into the preferred optimal adaptations of spatial cognition. In contrast to Ruddle and Lessels (2006a), the measured components here are not hierarchical, but they are on equal level with each other and the interaction between them reflects an efficiency trade-off set by the spatial strategies (Figure 23).

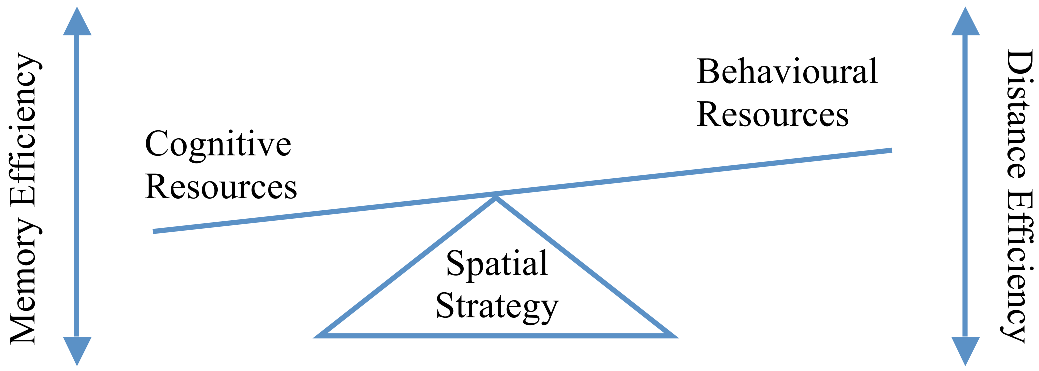
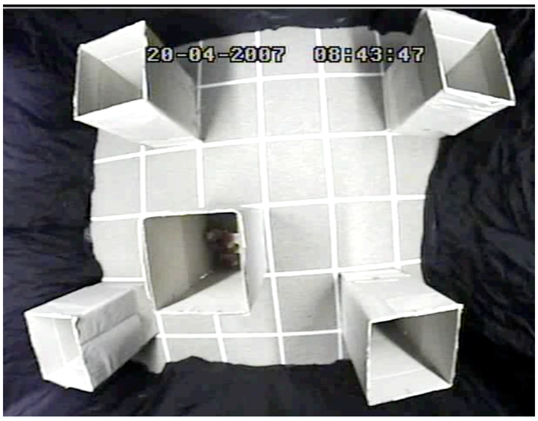


Figure 23. Schematic diagram of the optimal resource allocation as predicted by the M-D hypothesis. Cognitive resources are quantified by the memory measure and behavioural resources are by the distance measure. Efficiency trade-offs between the two measures are the consequences of the spatial strategies when either the cognitive or the behavioural resources are over- or underutilized.

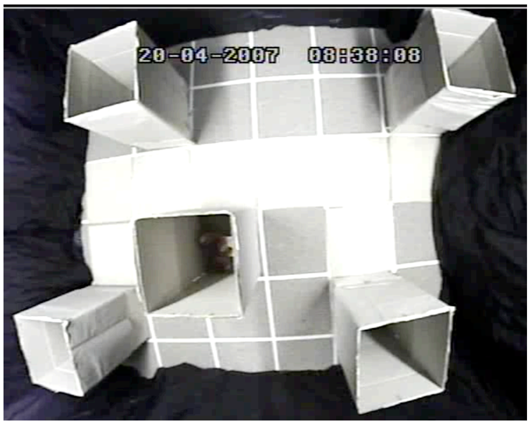
As discussed earlier, efficiency trade-offs (interactions) were found both in the unconstrained physical space (Chapter 2) and in the effortless virtual space (Chapter 4). In addition, the agent-based model in Chapter 5 could successfully simulate and give insight to the interaction observed in the first study (Chapter 2). The last study in Chapter 6 revealed a temporal interaction between learning from different website layouts and retrieval efficiency over time. These findings further support the M-D hypothesis claiming that human spatial cognition is optimized by trade-offs between cognitive memory costs of route-planning and the behavioural costs of travelling distances.

Environmental Biases

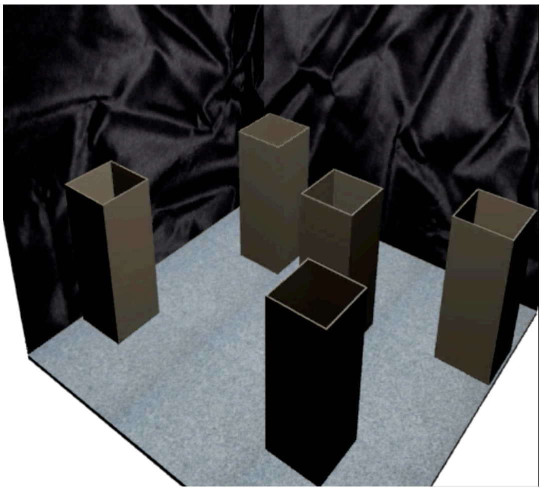
The third research question of this thesis was to investigate the role of the environment in spatial strategy selection. Spatial strategy optimizations and navigation performances from an unconstrained physical space and in three other spaces with the same internal layout in Chapters 2-5 were compared (Figure 24). The results showed environmental biases in the constrained YBR physical (Chapter 3) and in the effortless virtual space (Chapter 4) on how participants optimized their resources and how well they solved navigation tasks. In spaces, however, where the environment permitted unconstrained free exploration and navigation behaviour, as it was the case in Chapter 2 and 5, the spatial strategies were selected by individual preferences or styles.



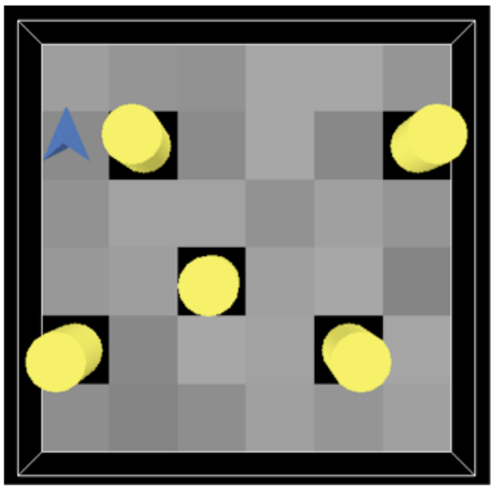
Unconstrained Physical Space (Ch.2)



Forced Axial YBR Space (Ch.3)



Effortless Virtual Space (Ch.4)



Computational Model Space (Ch.5)

Figure 24. Four different spatial environments with the same layout used in this thesis. Spatial strategy optimizations were biased by these environments in the YBR and in the virtual space compared to the baseline physical space and its simulation in the agent-based computational model.

As mentioned earlier, in the virtual space (Chapter 4), due to the minimal travelling costs, even circularly exploring participants with better acquired route knowledge travelled as much as single route-following axials. It is a consequence of the optimal adaptation rule of people to their changed task environments (Anderson, 1991). In other words, this suggests that a spatial environment that deviates from the properties of a free physical exploration (i.e., Chapter 2) will modify the way people optimize their spatial strategies.

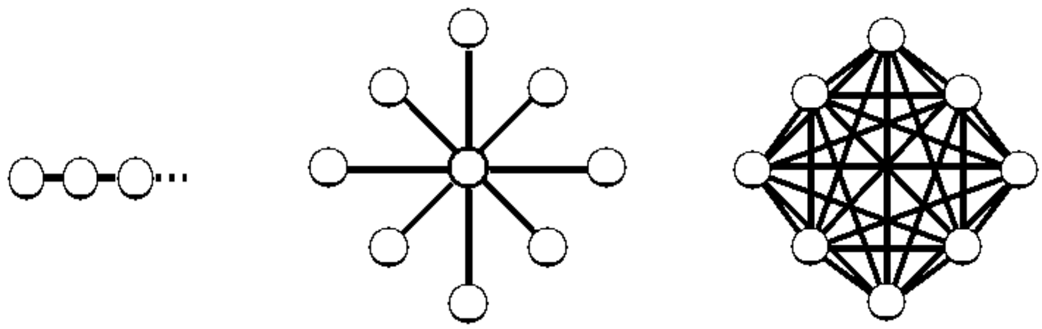
As per deviated physical spaces, Chapter 3 examined whether the route layout or individual navigation styles played a greater role in determining spatial strategies. Results with the forced exploration routes (Yellow Brick Road; YBR) showed that learning in a spatially restricted environment overwrote how efficiently participants utilized alternative routes (memory efficiency) during the subsequent navigation task, but not how much distance they travelled. Participants who were forced to explore using the circular YBR solved the task on fewer routes but overall with similar travel lengths as forced axials. This was an interesting mismatch between the results from the baseline study, where the axials were more memory efficient and the circulars were more distance efficient navigators. The proposed explanation related to the restrictive experimental manipulation within the spatial environment (i.e., forced axial/circular YBR patterns). The forced spatial learning prevented participants to freely optimize their cognitive and behavioural resources according to their individual preferences and they adopted to the strategies dictated by the external environment. This environmental bias is an extraneous effect of the forced spatial layout that overwrote individually preferred resource allocations. It reflects cognitive flexibility and adaptation to the environmental circumstances such as restricted exploration routes or low-cost travel options. As in the case of the forced axial explorers, a restrictive environment that does not provide alternatives to acquire extra spatial information could result in more subsequent deviations from the learnt route and decreased distance efficiency.

A better understanding of how the environment affects spatial cognition through spatial strategy optimizations complements the existing literature that has so far only described the interaction between humans and their spaces, but failed to explain the underlying psychological and cognitive mechanisms (e.g., Hillier, 1996). To become able to predict accurately how a spatial context is going to affect navigation performance and spatial decisions, it is essential to include an analysis of memory and travelling distance cost optimizations (M-D hypothesis).

Navigational Control

The last empirical chapter of this thesis presented a study that applied the findings from the previous chapters into a practical issue of instructional design of an e-learning educational program. The results demonstrated that the dissociation of the information foraging costs between acquiring and processing information on websites is analogous to the spatial strategy trade-offs according to the M-D hypothesis. This is according to expectations as the information space is often conceptualised in terms of a spatial metaphor with a strong environmental bias towards cognitive optimizations (Boechler, 2001). The spatial metaphor claims that both physical and informational spaces are semantically and spatially organised structures, whereby meaning and location are related properties. On the one hand, target objects in an experimental room and the nodes of an e-learning course carry information about their content (i.e., soft toys / educational materials). On the other hand, they are also signposts of the specific spatial location they occupy (i.e., box in the corner / second link on the right).

Chapter 6 revealed that semantics and structure in the information space interact with each other similarly to the physical space. Information retrieval rates and navigation performances were different between three e-learning layouts (Figure 25).



Axial layout Star layout Circular layout

Figure 25. Three e-learning layouts (axial; star; circular) used in Chapter 6. The nodes are individual websites and the connecting lines are hyperlinks.

Learners on the linearly structured axial website layout navigated more intensively than learners in a star or circular layouts to compensate for the limited control over the immediately available information. Consequently, axial learning was less distance efficient than the more flexible learning patterns with multiple route options and greater navigational control (i.e., star & circular).

The M-D hypothesis predicts a strategy trade-off between the allocation of available cognitive and behavioural resources during spatial cognition. In the e-learning study, a drop in cognitive optimization was therefore expected for the axial layout. The memory recall performances taken two-weeks after learning, in fact, demonstrated greater forgetting rates for the axials compared to the circulars. This suggests that information learnt in e-learning layouts with higher freedom over the control of navigation allow better consolidation and integration of the newly acquired knowledge into the relational memory than restrictive learning layouts.

However, the memory performances assessed immediately after the e-learning session showed an advantage for the axial group. This finding was in accordance with some previous research suggesting that simple web designs provide better recall rates (e.g., McDonald & Stevenson, 1996; Southwell & Lee, 2004). These interpretations assumed that cognitive load in a complex e-learning environment hinders learning performance did not factor in the increased distance costs of navigation in an otherwise simpler layout. Findings from this thesis also point out that the benefit of a simple layout is only short-term effectiveness, but not long-term efficiency. The increased cognitive effort in learning a structure in addition to the content material although limits the amount of immediately available learning outcome, but it helps consolidating the learnt material into the long-term relational memory system.

The last empirical chapter presents not only an applied domain, where strategy optimizations can be found (i.e., between the informational foraging and the navigational costs) as predicted by the M-D hypothesis, but also highlights a possible interpretation of why e-learning has not been as successful and widely accepted as it was hoped by its pioneers. The reason why many learning specialists and instructional designers consider classical e-learning as a failure could be largely attributed to the fact that the learnt material is mostly forgotten over time and it makes little permanent impact on the learner (Dror, 2008). Long-term goals were ignored not because of the lack of interest, but the lack of scientific research on key topics such as strategy optimizations presented in this thesis. Future applied research in this field should pay greater attention to how humans allocate their available resources in the informational space depending not only on cognitive load, but also on navigational control and environmental biases. Developing better learning and cognitive technologies that place the locally optimizing human cognizer in the centre of the learning process can benefit from the findings of this research (Dror, 2007; Dror & Harnad, in press).

Conclusion and Future Directions

The results of the studies reported in this thesis offer a functional description of how humans optimize their limited cognitive and behavioural resources when interacting with their spatial environments. In the light of the present findings, spatial cognition can be understood as a heuristic trade-off between cognitive costs of route-planning and behavioural costs of travelling distances set by locally optimal spatial strategies.

The observable manifestations of these spatial strategies are exploration patterns during the first interactions with a novel environment. The thesis identified two such specific patterns of initial spatial exploration (axial & circular); however, the shapes and numbers of these aggregate route representations might vary in other environmental layouts. Mobility patterns of people have been investigated in open large-scale and urban spaces with various other methods (e.g., González et al., 2008; Hillier, 1996), but without considerable effort to understand spatial strategy optimizations. Future research should complement these largely mathematical and technical approaches with that of the thesis to identify emerging spatial patterns and predict navigation efficiencies in both physical and abstract spaces.

There are plenty of potential practical applications that could stem out from these theoretical findings. Two examples were already mentioned, one with planning restrictive exploration routes in department stores (Chapter 3 based on Penn & Turner, 2001) and the other with finding efficient e-learning instructional designs (Chapter 6). These showed that the M-D optimization principle was useful in predicting how manipulation of user navigational control can affect learning outcomes. With careful considerations of the constraining environmental biases this principle can be generalized to any environment where individuals travel through space. One particular line of research that is concurrent to the M-D optimization applies spatial strategies to discrete optimization problems, such as the Travelling Salesperson Problem, and simulates highly successful heuristic human solutions (Makány & Makowsky, 2006). Those findings have direct relevance for applications in the areas of vehicle routing, global navigation systems, telecommunication, network architecture, or complex and managerial decision-making (Brusco, 2007; Chronicle et al., 2006).

Although the scope of this thesis was of individual navigators, future research needs to expand this on the effects of collective spatial cognition (Goldstone, Ashpole, & Roberts, 2005; Goldstone, Roberts, Mason, et al., 2008). As it was argued in the introduction, models and interpretations from both the macro (group) and micro (individual) levels are needed to comprehensively understand how people allocate their resources when interacting with their dynamic spatial environment. The importance of research linking individual spatial strategies with social mechanisms was also demonstrated in a model of crisis-driven ethnic migration (Makány, Makowsky, et al., 2006). These empirical findings suggest that the scientific theory of spatial cognition is related to very acute and sensitive issues in geo-politics and econometrics.

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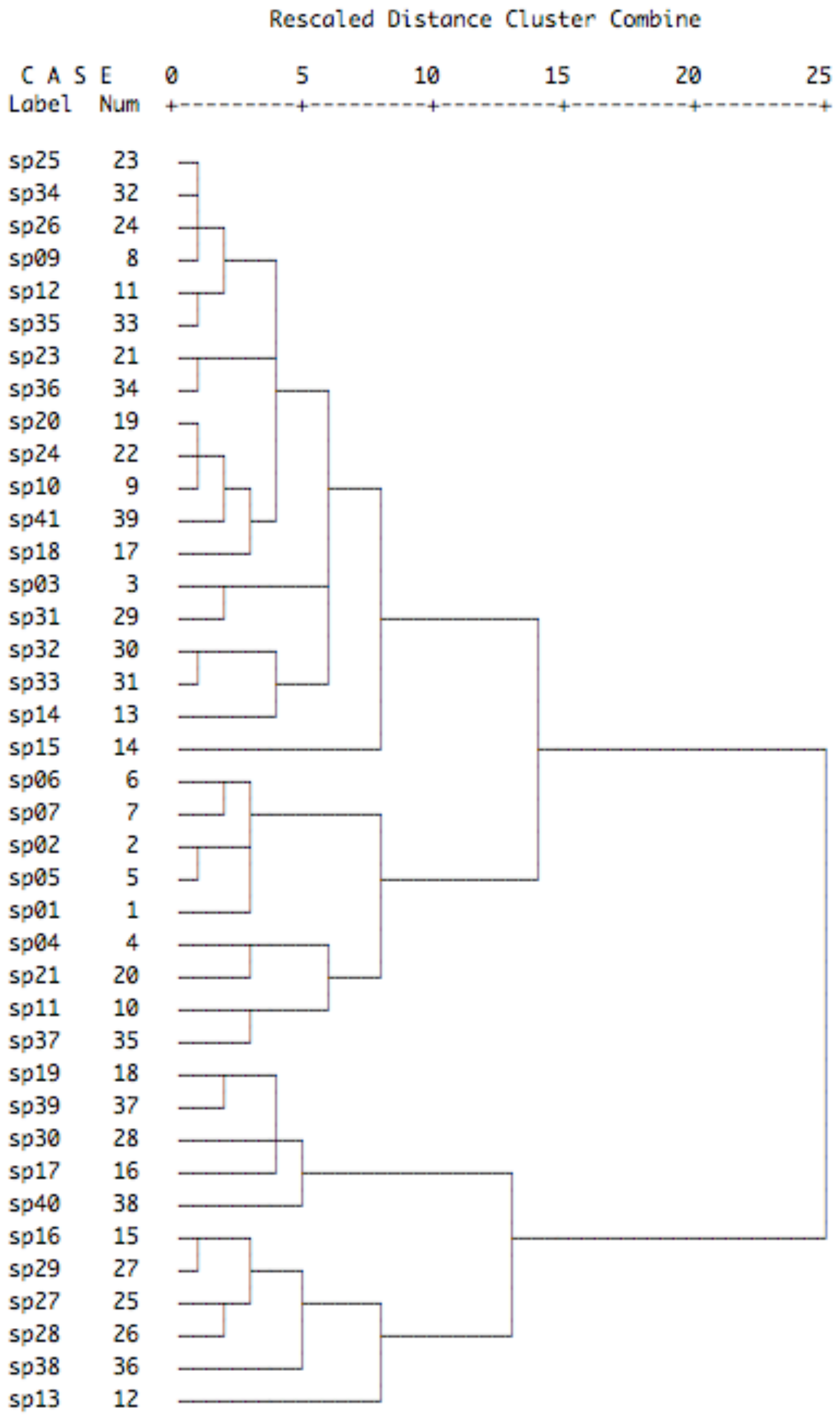
Appendices

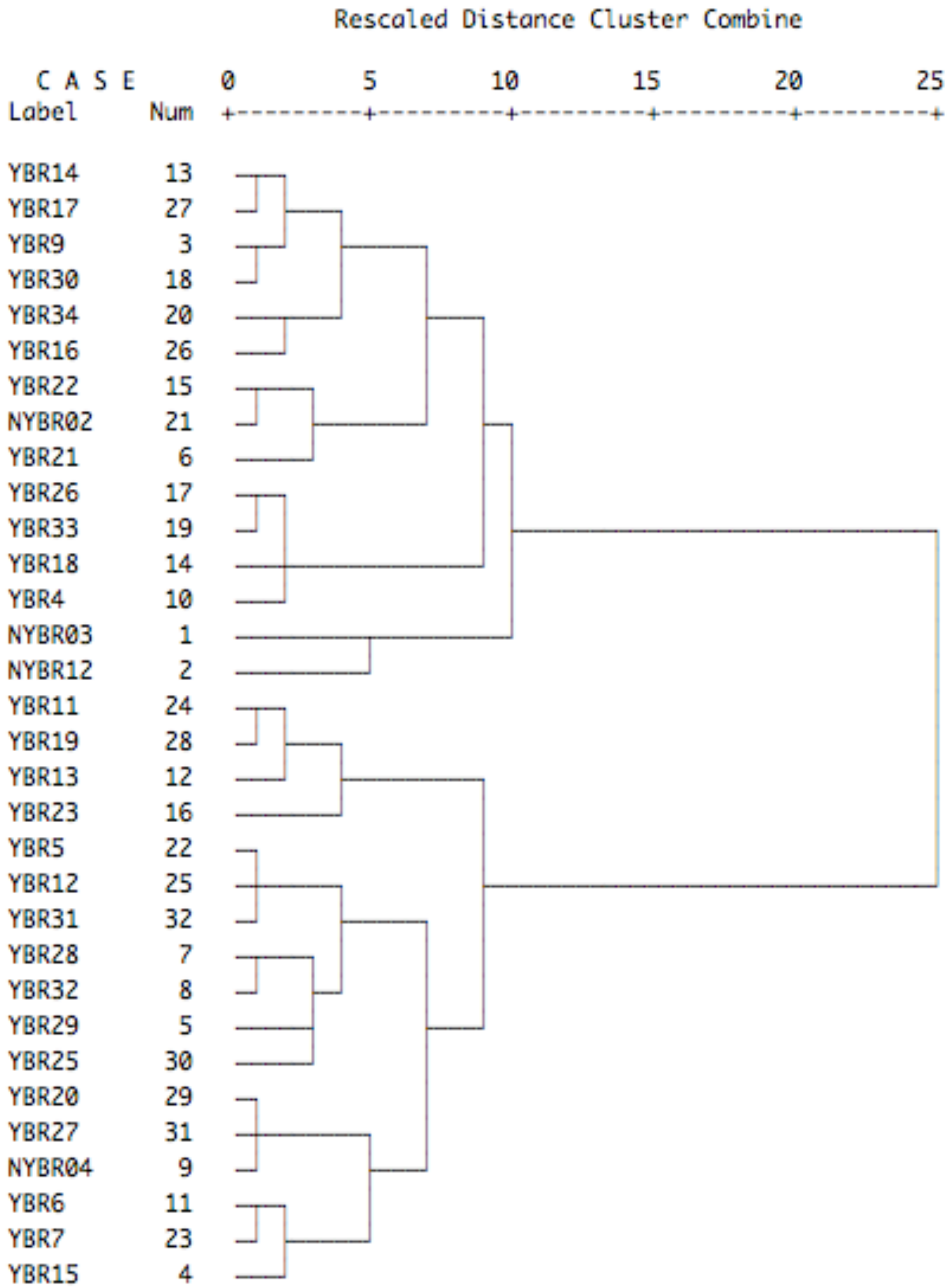
Appendix A

Dendrogram from the hierarchical clustering of the exploration matrices in the physical space in Chapter 2. This suggests two main cluster groups within the 38 valid individual cases.



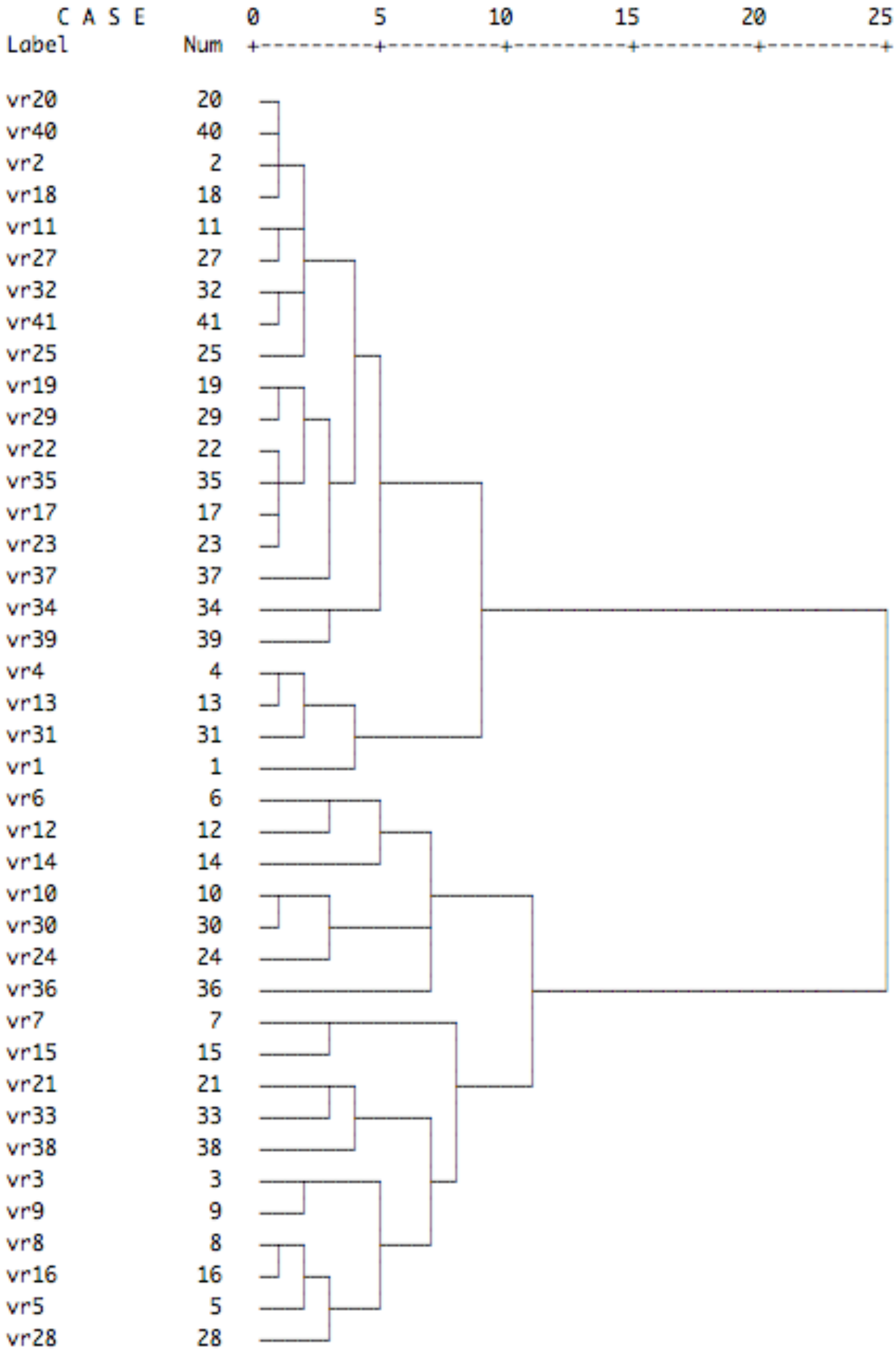
Appendix B

Dendrogram from the hierarchical clustering of the initial exploration patterns in the YBR experiment in Chapter 3. This suggests two main cluster groups within the 32 valid individual cases.



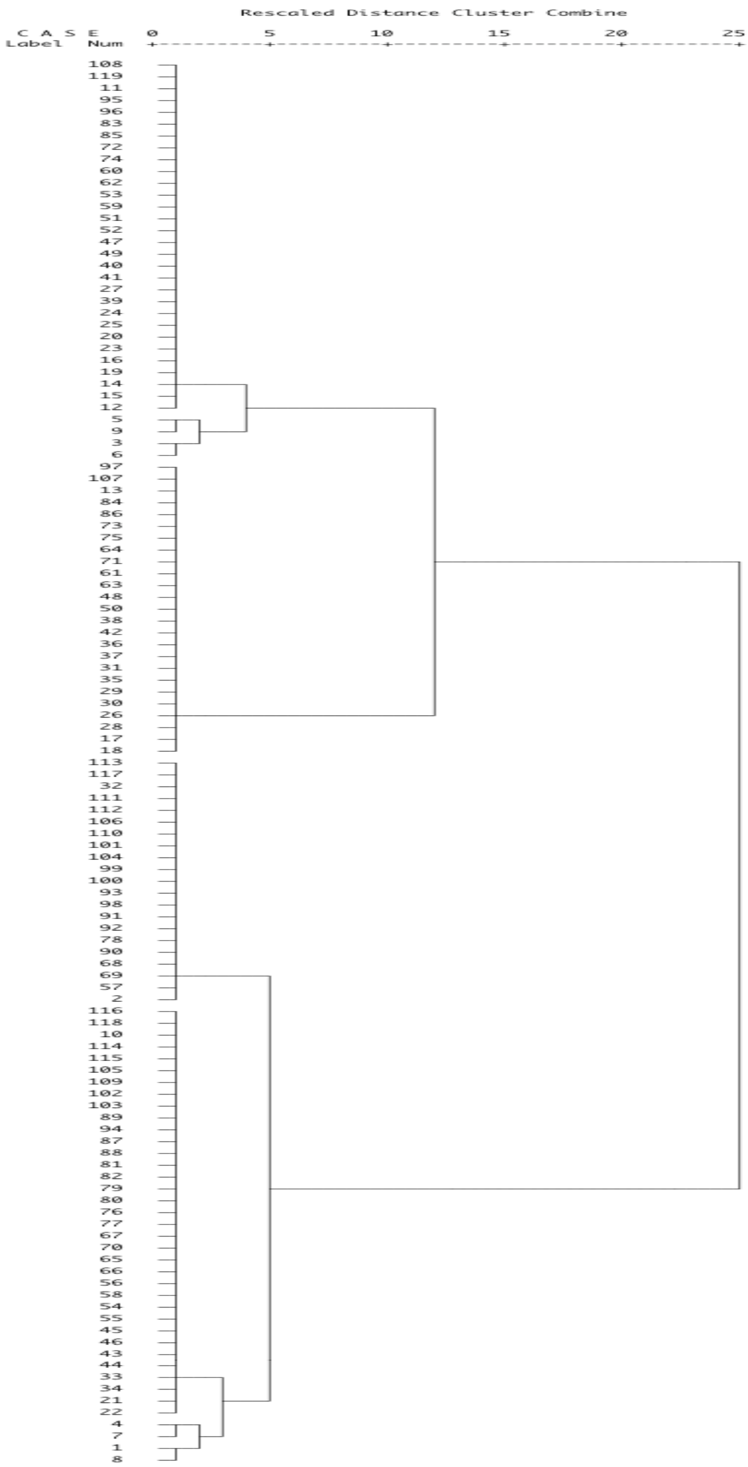
Appendix C

Dendrogram from the hierarchical clustering of the exploration matrices in the virtual space in Chapter 4. This suggests two main cluster groups within the 40 valid individual cases.



Appendix D

Dendrogram from the hierarchical clustering of the exploration matrices in the computational model space in Chapter 5. This suggests two main cluster groups within the 119 valid individual parameter sweeps.



Appendix E

Example of a single node ("Depth of Processing") in the e-learning experiment (Chapter 6) presented in an axial layout. Participants had low level of control as they could only navigate back to the previous page ("Incidental Learning") or forward to the next page ("State-dependent Learning") by clicking on the appropriate buttons. No option was offered to visit other pages and learn the information in alternative sequences.