UNDERSTANDING HUMANS' STRATEGIES IN MAZE SOLVING

FROM EYE-HAND COORDINATION

by

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ABSTRACT OF THE DISSERTATION

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Navigating through an overhead visual maze is a demanding task. It relies on the strategic use of eye movements to select and identify the route. Maze solving also makes demands on memory and vision, and requires frequent decision and plans. When solving a maze, there are trade-offs between spending time exploring to the environment and spending time learning from errors. The current study examined strategies used to solve novel and familiar mazes that were viewed from above and traversed by a mouse cursor. Recorded eye and mouse movements revealed two modes that almost never occurred concurrently: exploration and guidance. Analyses showed that people learned mazes and were able to devise and carry out complex, multi-faceted strategies that traded-off visual exploration against active motor performance. The results challenge the previous findings that people prefer to use the external world as an external memory and minimize the use of the own short-term memory. Instead, people balanced the use of memory and the access to the external world, and this balance varied among different individuals. Overall, strategies of maze-solving took into account available visual information, memory, confidence, the estimated cost in time for exploration, and tolerance for error. Maze-solving provides an environment in which people have to continuously make decisions and plan paths in real time. By modeling the strategies people use, it is possible to draw inferences about many aspects of cognitive processes, such as the real-time decision making, the usage of memory in natural tasks and eye-hand coordination. The understanding of the strategies in maze solving may also benefit applications, such as designing navigation assistive devices and the development of methods to coordinate the interaction between human and machines (including robots) in road guidance.

Key words: maze solving, eye-hand coordination, eye movements, cognition, memory, attention

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1. General Introduction

Way-finding involves several cognitive processes, including memory, spatial cognition, learning and decision-making. With the developments in artificial intelligence and information technology, machines are now very good at planning routes (e.g., google maps, GPS). These machines usually compute all existing routes on the map and find the ones with the shortest distance or the shortest travel time. Human beings are also good at finding paths, but cannot do the same huge computation over all possible routes. The question here is: what makes human's way-finding behavior efficient, and what can eye movements reveal about the relevant processes? In order to address these two questions quantitatively, this dissertation used a maze solving task, in which stimuli could be well-controlled and the strategies could be revealed from eye-hand coordination.

Below, I will first review some previous studies, which aimed to understand the underlying cognitive processes through eye movements or eye-hand coordination. Then I will introduce my maze solving task.

1.1. Eye movements and underlying cognitive processes

Eyes are the window on the mind. In everyday life, we observe the surroundings and collect information about the environment through vision and eye movements. Activities, such as driving, playing chess, or reading, cannot be performed successfully without eye movements. With current technology, eye movements can be recorded precisely in both spatial and temporal domains. The critical question still exists: what can be learned from the recorded eye movement patterns? Can eye movement patterns tell us about underlying cognitive processes, such as memory, reasoning, emotion or intention?

These questions have been discussed for more than a century, highlighted by Yarbus (1967), who pointed out that "eye movements reflect human thought processes".

Viviani (1990) reviewed studies conducted before 1990 and offered an influential analysis of what can be learned about cognitive process from exploratory eye movements. The main point he made is that it is hard to understand cognitive processes from eye movement data, unless it meets several requirements. First, cognitive processes should operate serially, so that the step-by-step component could be fully linked to the eye movement sequence. Second, a theoretical framework, which could explain the possible nature of the cognitive processes, should be built before investigating the exploratory eye movement data. Third, it was necessary to show that attention coincides with the direction of the line of sight.

In the past 20 years after Viviani's review, researchers have made efforts to address Viviani's concerns. One direction is to build up a framework of cognitive process before interpreting eye movement data.

A framework to model eye movements and visual working memory was the Oculomotor Geometry Reasoning Engine (OGRE), developed by Epelboim and Suppes (2001). According to the model, the capacity (how many items are stored) of visual working memory is filled quickly at the beginning of problem solving. The items stored can be overwritten with new items by scanning new regions, or with the same old items by rescanning the old regions. The OGRE model proposed that the capacity of visual working memory can be estimated by using the number of fixations between an initial visit and a re-visit to the same location. This model has been supported by some other studies. For example, Kibbe and Kowler (2011) used the OGRE model to estimate the capacity of working memory in a category search task and found the capacity (M) of working memory to be 4-6 objects. M varied across the category rules (different combinations of same and different features) and motor demands (manual search vs. oculomotor search with or without imposed delays).

Others proposed frameworks for modeling eye movement patterns in a visual search task, for example, the Bayesian ideal searcher model for searching for a Gabor on a computer screen, developed by Najemnik and Geisler (2005), and the entropy limit minimization (ELM) searcher model of searching for a Gabor developed by Najemnik and Geisler (2009). The Bayesian ideal searcher computes the posterior probability for all potential locations by weighing the detectability (how well the target could be detected at a certain location) and the visual template response at each location. Then, the ideal searcher selects the location that maximizes the probability of finding the target. The entropy limit minimization (ELM) searcher, which is even simpler in computation, selects the location with the lowest entropy (uncertainty). The entropy is calculated from the detectability at each potential target location. The next fixation should be the one that results in the highest reduction of entropy. These models predicted the eye movement patterns (median number of fixations to locate the target correctly; the distribution of fixations across the search area; the distribution of saccade lengths) by modeling the underlying computations. These computational models produce similar patterns as human eye movements – the numbers of saccades people would make to find the target and the spatial distribution of the saccadic landing positions. These studies addressed at least two aspects of Viviani’s criticisms. One, they built up a reasonable framework to account for the underlying process that determines where we look. Two, it gave a possible solution about how information is collected by eye movements and how previous knowledge (priors) and new visual inputs influence each other.

The models reviewed above link the eye movement patterns and cognitive mechanism. Many computational models were proposed in the area of memory or search (Kong, Schunn & Wallstorm, 2010). This could be because that cognitive mechanisms of visual memory and search have been studied better, compared to other high-level cognitive processes, such as planning, reasoning, emotions or intentions. These inspirational findings facilitate the modeling procedure. Computational modeling is an efficient way to examine hypothesis of how cognitive processes work by fitting real eye movement patterns with models. If the model fits the observed data patterns poorly, then the resulting hypotheses about the cognitive process behind this model could be regarded as bad assumptions and ruled out. When the model fits the data well, the model could be considered one possible ways (but not the only one way) to explain how the cognitive processes work. It is necessary, and very important, to evaluate whether such frameworks are accurate models of how the corresponding cognitive processes work.

1.2. Eye-hand coordination

Given the techniques developed, it is possible to measure the eye movements while doing natural tasks and not limit subjects to a static state where any body movements and head movements were restrained, as is usually done in eye movement research. This may lead to a new and more natural environment to study the function of eye movements. Recently, studies of eye-hand coordination have added a new dimension (hand) as a way to unearth underlying cognitive processes. It is well known that there is a collaborative pattern between eyes and hands: the eye usually searches for the target, and then guides the hand (e.g., Ballard, et. al., 1995; Epelboim, et. al., 1995; Flanagan, et. al., 2003).

Studies used sequences of eye movements to address the question of how people rely on the memory to solve visual problems involving eye-hand coordination. For example, Ballard, Hayhoe and Pelz (1995) examined the features of working memory capacity during a block-copying task (copying different patterns of colored blocks). The eye movement pattern showed that the most frequent scanning strategy used was the "model-pickup-model-drop" order. First, the eye fixated the block about to be worked on in the model to get the color of the block before picking up the same block from the resource pool. Second, it fixated the block in the resource pool to pick up the block. Third, the eye fixated at that block in the model again to get the location information. And finally, the eye fixated in the corresponding location in the workspace to drop the block there. This sequence suggested that subjects scan to get the information just before using it. Instead of fully using memory (e.g., about 4 items in visual memory), people prefer to use minimal memory and revisit to get information. This "just-in-time" strategy shows that even for the same block, subjects did not remember the color and location at the same time before manipulating it. Instead, they searched for the color information and location information separately, and just before using such information.

Flanagan and Johansson (2003) studied how human beings understand others' actions by observation. They used a block stacking task – three blocks were required to be placed in a certain order from the right part to the left part of the screen. They found a gaze predictive pattern – gaze landed at the ongoing grasping target slightly before the index finger landed at the grasp location. This pattern appeared whenever subjects were moving the blocks themselves, or observing others move the blocks. When there was no hand appearing as a cue of block movements, eye movements were reactive to the block movements, namely, the eye landed at the target only when the target started moving. These results indicated that eye movements are predictive of the hand movements. Eye movements could be a predictor of motor action, which may help to guide the motor system to the right location. Such a predictive function is also observed in the block-copying task (Ballard, Hayhoe and Pelz, 1995), which also showed that eye arrived at the corresponding location earlier than hand when picking up or dropping the block.

The block-copying task and the block-stacking task provide useful measuring tools to examine underlying cognitive processes. In these tasks, the cognitive processes are conducted in a serial way, in which it might be possible to map each cognitive process to each eye movement. The serial sequence gives the possibility of analyzing the cognitive processes moment-by-moment, and links the underlying cognitive processes and eye movements point-to-point. However, it still has shortcomings that the cases are too special to relate to general principles of planning or visual working memory. Color and space (location) are continuous that cannot be encoded efficiently, since they are continuous and may not have precise coding. It still remains as a question, how to measure information collected by eye?

In the above two subsections, I reviewed two main directions of recent studies about how to reveal cognitive processes through eye movements. One direction consists of building up a theoretical framework (Epelboim and Suppes, 2001; Najemnik and Geisler, 2005, 2009; Kong, et. al., 2010), and the other consists of finding a task which could sequentially map cognitive processes to eye movements. Both of these two directions achieved significant progress. However, most tasks studied so far were either fairly simple, or very difficult to model. Now, I'll introduce another task, maze solving, which might be a good tool to examine cognitive processes through eye movements.

1.3. Maze solving

The ability to plan a route and to find a route in a complicated environment is very important for human beings. To address the question of how people plan or find a route efficiently, various types of studies have been conducted, including animal maze studies, studies about the sense of direction and distance in blindfolded people (Worchel, 1951; Wang & Spelke, 2000), and navigation studies in virtual environments (Hamid, Stankiewicz & Hayhoe, 2010).

Unlike animals (e.g., rats and bees), humans might not have a magnetic sense of direction (Gould & Able, 1981; Westby & Partridge, 1986), therefore, finding a path must be based on memory and local cues. Early findings from studies using a triangle completion task, in which subjects were blindfolded and guided in one direction and then a second direction, and then asked to return to the original location, showed that the distance errors increased as the triangle size increased, suggesting that the error accumulates along the path (Worchel, 1951). Wang and Spelke (2000) further pointed out that, instead of using a static cognitive map to store the entire environment, human beings are more likely to keep updating their current location relative to individual landmarks on the route. Recently, way-finding behaviors have been studied in virtual environments focusing on the role of layout and landmarks. Newman et al. (2007) examined the transfer of environmental knowledge during a navigation task in computer-rendered towns. They found the best transfer when nothing changed, some transfer when either buildings changed or both targeted stores and surrounding buildings changed, and poor transfer when all landmarks changed. The transfer was even poorer when the previous association of layout and landmark was broken. This suggests that both layout and landmarks contribute to navigation. Hamid, Stankiewicz and Hayhoe (2010) studied the role of eye movements in encoding the landmarks within virtual maze-like environments. They found that landmarks located at hall ends, T-junctions or L-junctions, were viewed longer than those located in the middle of the hall, or on the side of the hall ends. They also found that performance was impaired when the landmarks viewed for the longest durations were removed. They concluded that people encode landmarks selectively in navigation, which makes the navigation simple and efficient. Measurement of eye movements thus could provide a clue about which locations were selectively encoded.

Differences in path integration performance could be predicted by a self-reported sense of direction (Wolbers & Hegarty, 2010; Hegarty, et. al., 2002; Kozlowski & Bryant, 1977; Sholl, 1988), which suggests that people are aware of their navigation skills. Human' navigation ability differs widely. During a navigation, some persons rely on geometrical cues (such as layout structures), while others prefer to use featural cues (such as landmarks) (Sandstorm, et al., 1998). Gender difference and age difference may also affect navigation. Cazzato et al. (2010) examined the gender differences in path planning by tracking eye movements. Subjects were asked to travel from a start location to a destination and pass over 7 sub goals on a map with a grid of seven vertical and five horizontal roads. They found that males were more likely to switch heuristics while females were more likely to stay with one heuristic constantly. They concluded that there is a trade-off between the execution and optimization in path planning, and that males seem to be more skillful in adjusting the previous made decisions in path planning and executing process.

Maze solving is a task that requires people to find a path. Given the structure of mazes (paths are equally spaced and the size can be controlled), performance can be measured quantitatively. Mazes have been used frequently in psychology and neuroscience. Most of these studies were done with animals, such rats. Crowe et. al. (2000) studied how human solve mazes by tracking their eye movements. Subjects were asked to find the correct path by scanning and fixating at the exit. They found that the solving time was strongly correlated with several parameters of the maze, such as the path length and the number of turns. They also pointed out that fixations played a crucial role in finding the paths – they found the length of the path was highly correlated with and could be predicted by the numbers and durations of fixations. Thus, they believed that eye movements could disclose the underlying cognitive processes related to the maze solving task.

Crowe et. al. (2000) is the only study I found that investigated how human solve overhead mazes on a computer screen. However, by only tracking the eye movements, lots of information is lost. Eye scanning is a very fast process and one single fixation spot could be used for many purposes, such as exploring for new information, checking the existing but not ensured information, or just getting distracted. It is hard to map complicated cognitive processes to such a measure. Even if such mapping can be done successfully, it is still not a natural way to ask people to solve the maze, just by eye.

1.4. The Current Study

A human being solving a maze also relies on vision and on memory to decide which path to take. This is evident when solving an overhead maze with the hand or a mouse. In order to solve the maze quickly, people need to trade-off scanning ahead with the eye for more information, and so relying on memory to store the correct path, vs. a strong reliance on immediate visual cues, at the risk of time-consuming errors. When trading-off scanning ahead for information vs. immediate visual guidance, people may take into account memory load, as well as the precision of the visual information at each scanning spot. An outcome of this trade-off determines the strategy people choose. Studying eye-hand coordination during maze solving should be a good way to determine the strategy. Understanding the strategies humans use for maze-solving is valuable for applications in cognitive neuroscience, such as understanding the mechanisms that determine the optimal use of resource in natural tasks.

By tracking both eye and hand movements, the current study aims to reveal different cognitive strategies, as well as underlying cognitive processes from perceptual-motor cooperation. I expect that different strategies, which take into account multiple cognitive processes (memory, available visual information, decision making of trade-offs) could be revealed by the change in eye-hand coordination patterns and open the way for new theory of human’s navigation.

In this dissertation, I will report three experiments which studied strategies used in maze-solving task. In the first two experiments, in order to examine whether subjects learned the maze, each maze would appear twice in a row – a training trial followed by a testing trial. The maze in the testing trial was: (1) exactly the same as the trained maze (forward condition); (2) the same as the trained maze with the start and the end locations switched (backward condition); and (3) the trained maze rotated 180 degrees (rotated condition). The learning effect I studied is whether the knowledge of the maze could be transferred from training trials to testing trails.

Experiment 1 examined the characteristics of the strategies in maze-solving task and the difference of the strategies subjects used when subjects were told (with expectation) or not told (no expectation) that two trials with the same maze will be presented. Experiment 2 examined how to improve learning by asking subjects in the training trials only to scan the mazes for a certain duration and not to travel in mazes at all. I will also analyze data from both experiments in order to address answer the question that what makes people decide to switch from one mode to another in their strategies. Experiment 3 varied the size of the visible window around the mouse, and examined the efficiency of gathering information and the change of the strategies with different sizes of the visible window.

2. Experiment 1 (Expected vs. Unexpected)

2.1. Methods

2.1.1. Subjects

Twenty subjects were tested, 18 undergraduates recruited from the General Psychology subject pool who earned course credits, and 2 paid volunteers. All subjects had normal vision and were naive as to the purpose of the experiments. The procedures were all approved by of the Rutgers University Institutional Review Board for the Protection of human subjects.

2.1.2. Eye movement recording

Eye movements were recorded using the Eyelink 1000 (SR Research, Osgoode, Canada) tower mounted version, sampling at 1000 Hz. A chin rest was used to stabilize the head. Eye movements were recorded from the right eye.

2.1.3. Stimuli

Stimuli were presented on a Viewsonic G90fb CRT monitor, 1024×768 resolution, 60 Hz refresh rate, located at a viewing distance of 119 cm. The display area subtended 16.2° horizontally by 12.3° vertically.

Stimuli were square 12 unit by 12 unit mazes (10 deg $\times$ 10 deg), centered on the screen (Fig. 1). The start location, marked with a green circle, was assigned to one of the four corners of the maze and the end location, marked with a blue circle, was always the opposite corner.

Sixty mazes were generated by a free random maze generator (written in the python language by Georgy Pruss, 2003, http://code.activestate.com/recipes/578356-random-maze-generator/). Since the maze were randomly generated, the difficulty was expected to vary (a behavioral measure of difficulty will be described below). All mazes were drawn with white lines as walls on the black background. The mazes were randomly assigned one of four possible start locations (upper left corner, lower left corner, lower right corner or upper right corner). The maze was navigated by using a mouse to control the movements of the red cursor.

2.1.4. Procedure

Each subject was tested in 6 sessions. Each session contained 20 maze trials and two calibration trials, one at the beginning and one at the end of the session. In the calibration trials, subjects were asked to look at and click the mouse on each corner of a 8.3 deg $\times$ 8.3 deg square. These calibration trials were used to verify the accuracy and precision of the mouse and eye signals, supplementing the built-in Eyelink 9-point calibration routine.

Before every maze trial, subjects were asked to fixate at a central cross and click the mouse to start the trial when ready. One second later the start location (green disc) and the end location (blue disc) appeared on the display. Subjects moved the cursor (red disc) to the start location (green disc) and clicked on the disc. After a 500 ms delay, the maze appeared and subjects could begin to use the mouse to navigate the cursor in the maze from the start location to the end location. Once the cursor reached the end location the trial would end automatically (See the procedure in Fig. 2b, using a small maze for illustration purposes).

Each maze was solved twice consecutively. The first trial of each pair was the "training trial" and the second trial of each pair was the "testing trial". Thus, each subject ran 60 training trials and 60 testing trials.

Experimental Conditions

There were three different types of spatial relationships between the mazes in training and testing trials (Fig. 2a): (1) *forward condition*, in which the testing trial used exactly the same maze as the training trial; (2) *backward condition*, in which the testing trial used the same maze as the training trial, but the start and the end locations were exchanged; (3) *rotated condition*, in which the maze in the testing trial was rotated 180 degrees from the maze in the training trial, and the start and the end locations remained at the same positions on the screen. Figure 2a illustrates these three conditions, using a small maze (4×3) for illustration purposes.

To assign mazes to the 3 conditions, the following was done:

All 60 mazes were first labeled from 1 to 60 based on the random order in which they were generated. The first 20 mazes were assigned to the forward condition, the second 20 mazes to the backward condition and the remaining 20 mazes to the rotated condition. Then, to determine the order of testing the 3 conditions over the 60 training trials, the 60 mazes were sorted again based on a list of 60 random numbers generated by MATLAB. All subjects used this same order. Ten mazes were tested in one session (20 maze trials in each session, each maze repeated twice) and there were 6 sessions in total.

This means in each session, the order of the mazes to be tested and the assignment of conditions was fixed. For each individual subject, the order of testing the 6 sessions was randomized.

Subjects were divided into two groups. The Expected group (n=10) was notified that two consecutive trials with the same maze would be tested. The Unexpected group (n=10) was not told that the maze would be tested twice (although they may have guessed this) (Newman, et. al., 2007). Subjects in both groups were instructed to solve the maze as fast as possible.

2.1.5. Analysis

Mouse positions were recorded in every refresh frame. Mouse signals were filtered at 10 Hz frequency (Flash and Hogan, 1985).

The beginning and ending positions of saccades were detected offline by means of a computer algorithm employing a velocity criterion to find saccade onset and offset. The value of the criterion was confirmed for individual observers by examining a large sample of analog recordings of eye positions.

One subject in the Unexpected group lost 47% of the data due to blinks or loss of tracker lock. This subject was therefore removed from data set used to analyze eye movements. The remaining 19 subjects had about 5% of data lost due to blinks or loss of lock (6.12% for the Expected group, and 4% for the Unexpected group). To confirm that the outcome was not biased by instances of blinks or loss of lock, I analyzed the mouse performance using both the complete dataset (including any parts where the eye trace was lost) and the lock-lost free dataset. The patterns between these two datasets were very similar. (See Appendix for the comparison between the complete data and the lock-lost free data, with further discussion in sections 2.2.2.3 and 2.2.2.4).

2.2. Results

2.2.1. Solving time in training trials

The time taken to solve each maze was determined for the training trials in the Expected and Unexpected groups. The average solving time for each of the 60 mazes (n = 20 trials/maze) is shown in order from fastest to slowest in Fig. 3A. This order served as an index of maze difficulty, i.e., the shorter the initial solving time, the "easier" the maze is. Initial solving time increased approximated linearly across the 60 mazes. As the initial solving time increased, the variability (individual differences) of subjects' performance also increased. Fig. 3B shows the mean solving time for each subject, sorted from shortest solving time (fastest subject) to longest solving time (slowest subject). Comparing Figs. 3A and 3B show that the range of individual differences was slightly less than the differences due to maze difficulty, i.e., RT as a function of maze difficulty covered a larger range than RT as a function of subject.

Inspection of the mazes suggested that several characteristics accounted for why some mazes were more difficult than others: total path length, the numbers of turns, and the presence in the maze of long "blind alleys", which, if entered, required time (back – tracking) to return to the correct path. Given that so many different factors accounted for difficulty, the difficulty order based on the travel time empirically determined (Fig. 3A) will serve as the index of difficulty to be used when reporting the results below.

2.2.2. Analysis of Strategies

2.2.2.1. Eye-mouse coordination patterns: basic features

Inspection of the recordings of eye and mouse movements suggested two modes of performance that are very different from each other: *exploration*, in which saccades were made to search for the correct path while the mouse was stationary or nearly stationary, and *guidance*, in which saccades guided the mouse along the chosen path while the mouse was moving. Guidance episodes were highly stereotypical, with the eye executing sequences of saccades along the path and almost always leading the mouse (Johansson et al., 2001; Flanagan & Johansson, 2003). Exploration was idiosyncratic. Some trials showed extensive exploration with saccades before beginning to move the mouse. Other trials showed episodes of exploration during the trial after the mouse began to travel the maze. Fig. 4 shows examples of these two coordination patterns in the traces of eye and mouse movements.

The differences between exploration and guidance can also be seen in plots in which the eye and mouse traces were superimposed on the maze. Fig. 5 shows several frames from a dynamic plot of eye and mouse positions on the maze. In the exploration mode (Fig. 5A), the mouse (blue line) slowed down or stopped while the eye (red circle) was sent out to search in the maze. In the guidance mode (Fig. 5B), the eye (green circle) jumped ahead and waited for the mouse to catch up.

2.2.2.2. Distinguishing episodes of guidance and exploration

Although the difference between episodes of guidance and exploration can be illustrated by the eye and mouse traces (Fig. 4), as well as by the records and movies of the eye and mouse movements (Fig. 5), it is also necessary to formally define and describe the differences between these two episodes in order to better understand the strategies of maze navigation.

After examining a large sample of trials, two main factors were found that appeared to characterize exploration and guidance modes: the speed of the mouse movement and the distance between the eye and the mouse.

During the guidance episodes, the mouse usually moved, while during exploration, the mouse was relatively stationary. Thus, each fixation period (the interval between successive saccades) was provisionally characterized as guidance or exploration on the basis of the speed of the mouse movement during that segment (mouse trace length / duration of fixation). The distribution of mouse speeds in each fixation is plotted in Fig. 6. The shapes of the distributions suggest a combination of a gamma distribution for slow speeds (from 0 to the bottom of the valley ~ 70 pixels/s) and a Gaussian distribution for faster speeds (greater than 70 pixels/s). The Gaussian distribution part, with a mean speed about 200 pixels/s, may represent the mouse movements during guidance. Based on the valley in the distribution, 70 pixels/s was selected as the speed criterion: any episode in the fixation pause in which the mouse speed was greater than 70 pixels/s was provisionally labeled as “guidance”.

Guidance episodes also showed a stereotypical pattern in which the eye jumped ahead with a saccade, the mouse caught up to the eye during the fixation pause, and then eye jumped ahead again in the following saccade. Thus, the change in the distance between the eye and the mouse increased during the initial saccade, decreased during the fixation pause, and increased again at the offset of the following saccade. Fig. 7A (panel a, b, c) verifies this pattern. It shows the change in the distance between the eye and the mouse during three intervals: during the saccade preceding the fixation pause (Fig. 7a), during the fixation pause (Fig. 7b), and during the saccade following the fixation pause (Fig. 7c) for guidance episodes. As the histograms show, the eye-mouse distances increased during the first saccade, decreased during the fixation pauses where the mouse was catching up to the eye, and increased during the final saccade, as predicted to be the pattern during guidance.

Fixation pauses with mouse speeds less than 70 pixels/s may be more complicated. These could be the explorations, where the mouse slowed down and the eye was sent out to explore. It could also be other patterns. For example, there were a small proportion of fixation pauses in which the mouse stopped or moved very slowly while the eye was very close to the mouse. Those episodes were assumed to be dealing with difficulties of controlling the mouse itself, and thus should be categorized as part of "guidance" saccades. Thus, for pauses in which the mouse speed was less than 70 pixels/s, the eye-mouse distance was used to further categorize the pause. If distances between eye and mouse at the onset and the offset of the fixation were both smaller than the width of the path (50 pixels), the fixation was labeled as "guidance". Otherwise, it was labeled as "exploration". One special case is fixations prior to the very first movement of the mouse. These were labeled as exploration, regardless of mouse/eye distances (see Table A-1 for the classification between Exploration and Guidance).

Exploration fixations were further labeled as "early exploration" (before the mouse began moving for at least two consecutive fixations, i.e., before onset of guidance) and "later exploration" (after the first occurrence of "guidance"). Fig. 7B (d, e, f) shows the change in distances between the eye and the mouse during the saccade before the fixation, during the fixation, and during the saccade after the fixation during what is classified as late exploration. These results show that during the first saccade, the distance often increased (because the eye usually jumped away from the mouse to explore), or occasionally decreased, as the eye jumped back toward the mouse. During fixation pauses, since the mouse was stable, the distance between the eye and the mouse did not change. During the saccade following the fixation pause, the eye either jumped further away (the distance increased), or jumped back (the distance decreased).

The patterns during early exploration (prior to any guidance) are similar to late exploration (Fig. 7g, h, i). The main difference is that during the first saccade (Fig. 7g), the eye could start from any location in the maze, instead of always jumping away from the mouse, so the distance difference between eye and mouse could either increase or decrease.

The information in Fig. 7 was then used to re-classify some fixation pauses that were initially labeled as exploration on the basis of mouse speed. Specifically, isolated fixation pauses labeled as exploration were re-examined. It seemed unlikely that exploration would last only for the duration of one fixation pause. Thus, the only single pauses considered to be exploration were those in which the saccade preceding the pause resulted in an increase in the distance between the eye and the mouse, and the saccade following the pause resulted in a decrease in the distance between eye and mouse. In those cases, the eye first jumped ahead to explore and then jumped back to get the mouse immediately. If the eye/mouse distances did not match this pattern, the isolated fixation pause was labeled as guidance.

Guidance was segmented further into guidance when the mouse was on the correct path and guidance when the mouse was off the correct path.

Thus, there were five groups of fixations and saccades: early exploration; late exploration; on-path guidance; off-path guidance; and other patterns (“other” was small proportion, less than 0.6%). Labels of “early exploration”, “later exploration” or “guidance”, based on the mouse speed and the distances between eye and mouse during fixation, were also assigned to the saccade which occurred just before the fixation.

The time spent on early exploration per trial was calculated as the sum of the durations of exploration fixations before the first guidance fixation. The time spent on late exploration per trial was calculated as the sum of the durations of exploration fixations after the first guidance fixation. The time spent on on-path or off-path guidance per trial were calculated as the sum of the durations of guidance fixation when the mouse was traveling on (or off) the correct path. The remaining time (< 0.6%) was classified as “other patterns”.

2.2.2.3. Training trials

Fig. 8 shows how the total maze solving time was apportioned among the 4 phases: on-path guidance (green), off-path guidance (blue), late exploration (dark red) and early exploration (light red) during training trials for Expected and Unexpected groups. Time is plotted as a function of the maze difficulty order (see Fig. 3). The time spent in each phase is indicated by the width of each band.

Most of the time was devoted to on-path guidance. The on-path guidance time increased with maze difficulty, reflecting the longer paths and reduced mouse velocity due to the increased number of turns with difficult mazes. The off-path guidance time also increased with maze difficulty, as did Exploration (early and late). The Expected group generally spent more time on exploration than the Unexpected group, particularly Early Exploration. For the Expected group, Early Exploration increased with maze difficulty. For the Unexpected group, Early Exploration was relatively flat across different maze difficulty levels. The longer exploration time in the expected group led to overall longer solving time, but it also contributed to decreasing the time spent in off-path guidance. This suggests that, exploration was useful in finding the correct path and avoiding time off the path.

Although the time spent on off-path guidance in the Expected group was less than in the Unexpected group, the difference was small. This suggests that the effect of the time spent on exploration in the Expected group was not to avoid the errors in the current trial, but rather to get and save information about the maze to be used in the subsequent test trial, where the same maze would be presented. This conjecture will be examined in the next section.

2.2.2.4. Testing trials

Fig. 9 shows how time was apportioned among the 4 patterns in the testing trials for both the Expected and Unexpected groups. The columns show the three different spatial relationships between the training maze and the testing maze (see Fig. 2): forward (left plots); backward (middle plots); rotated (right plots).

The patterns in the testing trials were different from the training trials in that the time spent in each episode did not vary according to the maze difficulty. Also, the time spent in the different phases also depended on the spatial relationship between training and testing mazes.

One trend that can be seen as that off-path guidance took up more time in the rotated condition than the other conditions, but off-path time decreased as the difficulty of maze increased. This pattern might have occurred because for the easy mazes, subjects recognized the rotated maze, which led to a greater reliance in memory, and more errors. For the hard mazes, subject might not have recognized them easily, so they treated the test mazes as new ones. As a result, there was more late exploration with the difficult rotated mazes.

The overall effects of spatial relationships between train and test mazes can be seen in Fig. 10, which shows the mean times spent in each phase averaged over all maze difficulties. Compared to the training trials, the time spent in on-path guidance (green) in the testing trials was shortest in forward condition, and longest in rotated condition. In order to further compare the training trials and testing trials, a two-way ANOVA was first conducted within all training trials. The two factors examined in ANOVA test were: (1) group (Expected vs. Unexpected); (2) spatial conditions (forward, backward and rotated). It shows that only for Early Exploration, the difference between two groups (Expected and Unexpected) was significant. Other than that, there was no significant difference between two groups and among three spatial conditions in all phases (see Table A-2).

Since there was no difference on mean time for each phases among three spatial conditions (forward, backward and rotated) in training trials, when comparing training trials and testing trials, two-way ANOVAS were conducted separately for forward cases, backward cases and rotated cases (see Table A-3). The two factors examined in the

ANOVA test were: (1) group (Expected vs. Unexpected); (2) trial type (training vs. testing).

For the forward condition, the F-test shows that there were significant differences for Off-path guidance ($F=21.64$, $p<.001$), Late Exploration ($F=9.58$, $p=.003$) and Early Exploration ($F=11.45$, $p=.001$) between training and testing (see table A-3 for details). No significant difference was found for On-path guidance between training and testing. There was a significant difference for Early Exploration ($F=9.03$, $p=.004$) between Expected and Unexpected groups (see table A-3 for details). No significant differences were found in the other phases between the two groups (Expected vs. Unexpected).

For the backward condition, the F-test shows that there was a significant difference for Early Exploration ($F=5.87$, $p=.018$) between training and testing. No significant difference was found for the other phases between training and testing, showing less benefit of training in the backward condition. There were significant differences for Late Exploration ($F=6.96$, $p=.029$) and Early Exploration ($F=6.89$, $p=.011$) between two groups (Expected vs. Unexpected). No significant differences were found in the other two phases between different groups (see table A-3 for details).

For the rotated condition, the F-test shows that there was a significant difference for Early Exploration ($F=4.09$, $p=.047$) between training and testing. No significant difference was found for the other phases between training and testing. There were significant differences for Early Exploration ($F=5.3$, $p=.24$) between two groups (Expected vs. Unexpected). No significant differences were found in the other phases between different groups (see table A-3 for details).

Two-way ANOVAs were then conducted to compare the mean times in different phases in testing trials (see Table A-4 for details). The two factors examined in the ANOVA test were: (1) group (Expected vs. Unexpected); and (2) spatial conditions (forward, backward and rotated). F-test shows that there were significant differences for Off-path guidance ($F=21.61$, $p<.001$) and Late Exploration ($F=23.47$, $p<.001$) across the spatial conditions (see table A-2 for details). No significant difference was found for On-path guidance and Early Exploration among different spatial condition. No significant difference was found ~~in neither phases~~ between the different groups (Expected vs. Unexpected).

For On-path guidance, although the differences within all testing conditions were not ~~neither~~ significant, the patterns, ~~that~~ shortest for Forward and longest for Rotated, still can be observed and it suggests that learning affected how quickly the maze was traveled when on the correct path. Notice that in the rotated condition, the effect of learning was to slow down the travel time.

Pair-wised comparisons were further done in all testing conditions for Off-path guidance and Late exploration. For Off-path guidance, the forward condition was significantly shorter than the rotated and the backward conditions. Note that the time in off-path guidance was slightly smaller in the Expected group, suggesting that there were benefits of the greater exploration during training (Figs. 8, 10). ~~And~~ the late exploration time was significantly longer in the rotated condition and was significantly shorter in the forward condition than it was in the backward condition.

2.2.2.5. Exploration during the travel

Most exploration occurred near the beginning of trials. Fig. 11 shows the proportion of time spent in exploration as a function of the percentage of time elapsed in the trial for training trials and for testing trials. The proportion of time exploring was calculated as the number of fixations labeled as Exploration divided by the total number of fixations. The proportions were then averaged over all trials, regardless of maze difficulty, subjects and spatial relationships. Fig. 11 shows that most exploration happened at the beginning of trials, and became less frequent over time.

Results are similar when the total time spent in Exploration (rather than the number of fixation pauses) is examined. Fig. 12 shows the ratio of time spent on Exploration to the total time (time on Exploration + Guidance). The Expected group spent more time exploring than the Unexpected group during the first part of the trial. This was confined by restricting analysis to Early Exploration period, before any guidance (Fig. 13). The extra exploration time in the Expected group might be used for learning to reduce the errors in the current trial or when solving the same maze again in the test trial.

2.2.2.6. Correlations between Exploration and Errors

When solving a maze, subjects could either explore and learn enough information before moving the mouse to travel in the maze, or move the mouse directly and make errors. Both of these two strategies were used. However, errors cost time. If the mouse goes into the wrong path, it needs to move back out before entering the correct path, which is very expensive in time. On the other hand, using eye movements to explore would seem to have lower costs in time. If it is true that exploration is less expensive in time than errors, then in order to solve the maze, it might be efficient that people first explore to get enough information and then just travel on the correct path. Given the fact that the Expected group conducted more early explorations and had fewer errors compared to the Unexpected group, early exploration should be crucial to reducing the errors in both training trials and testing trials. Was Exploration the more efficient strategy? To address this question, I examined the correlation between the exploration and errors ("off-path guidance").

Fig. 14 shows the relationship between the proportion of time spent in exploration per trial and the proportion of time spent off the correct path per trial during the training trials. For the Expected and Unexpected groups, the correlation was examined: (1) between "Early Exploration" and "off-path guidance" (left plots); and (2) between "Late Exploration" and "off-path guidance" (right plots). Table 1 contains R scores and p values of correlations and slopes of best-fitting lines for each dataset.

The correlations between the proportion of time on Early Exploration and the proportion of time on off-path Guidance were negative, as expected, as was the slope of best fit line. The correlation and slope for Late Exploration was positive for the Expected group and nearly 0 for the Un-expected group. These results suggest that late exploration might happen when subjects entered the wrong path and had to switch back to exploration to gather correct information.

These results suggest that it is the Early Exploration that was the most helpful – the more time exploring in the early stage of trials, the less time was spent off the correct path. However, the shallow negative slope between the early Exploration and off-path

Guidance shows that early Exploration was helpful, but expensive. In order to reduce time on the incorrect path, subjects needed to spend about three times more time on Exploration.

Fig. 15 and Table 2 show the relationship between the exploration in training trials and the off-path guidance in the testing trials, to find out whether the benefits of exploration transferred from training trials to testing trials. These results show that the early exploration in training trials was associated with fewer errors in testing trials for both “Expected” and “Un-expected” groups. However, the benefits were much smaller than those within training trials in Fig. 14.

The time spent in late exploration in training trials, and the error in testing trials, were not correlated for the “Expected” group, but were negatively correlated for the “Un-expected” group. This shows some possible benefit of late exploration for learning with the Un-expected group.

In order to confirm that the correlation between the exploration and errors was not due to the effect of other factors, such as the maze difficulty or subjects’ individual differences, a partial correlation analysis was conducted. Each pair of trials (one training trial and one testing trial) was given an index of maze difficulty (from 1 to 60) based on the initial solving time (Fig. 3A), and an index of subject’s performance (from 1 to 20) based on the mean solving time for each subject (Fig. 3B). In addition, each trial was characterized by the proportion of time spent in early exploration, late exploration and off-path guidance. All values of these variables were converted into Z-Scores. A partial correlation analysis was conducted to examine the relationship between exploration and off-path guidance, controlling for the maze difficulty and subjects’ individual difference.

The partial correlation relationships were examined within trials, between (1) the "early exploration" in training trials and the "off-path guidance" in training trials; (2) the "late exploration" in training trials and the "off-path guidance" in training trials; (3) the "early exploration" in testing trials and the "off-path guidance" in testing trials; (4) the "late exploration" in testing trials and the "off-path guidance" in testing trials. In order to find out whether the benefit of exploration could be transferred from training trials to testing trials, the correlation relationship was also examined across trials, between: (1) the "early exploration" in training trials and the "off-path guidance" in testing trials; (2) the "late exploration" in training trials and the "off-path guidance" in testing trials. Table 3 lists the R scores and p values of partial correlation for each pair. The results confirmed those in Table 1 and 2, namely, within the same trial, early exploration was negative correlated with off-path guidance, while late exploration was positively, or not correlated, with off-path guidance. These correlations suggest that the early exploration did help to reduce the errors, and the benefit was not due to other factors, such as the level of maze difficulty or individual differences (Table 3).

The partial correlation analysis (Table 3) also shows that, across the trials, early exploration in training trials was negatively correlated with the off-path guidance in testing trials, but not as strongly correlated within training trials. Late exploration in training trials was not correlated with the off-path guidance in testing trials. It suggests that the benefit of early exploration might be transferred from training trials to testing trials.

2.2.2.7. Trials with no Early Exploration

As mentioned above, early Exploration was defined as any Exploration before the first Guidance. Early Exploration occurred in most trials. However, there was a small proportion of trials that had no early Exploration. Fig. 16 shows the proportion of time spent in guidance, on or off the correct path, between the training trails with and without the early exploration. The proportion of guidance on or off the correct path plotted in the figure were first computed for each maze, and then averaged across all 60 mazes. Fig. 16 shows that the total absence of Early Exploration increased the proportion of time spent in guidance off the correct path. These results confirm that early exploration helped to reduce the errors made when solving the maze. The difference between the case with Early Exploration and the case without Early Exploration was larger for the Expected group than the Un-expected group.

2.2.3. Individual Differences

There were large individual differences in strategies used by subjects. Some subjects explored the maze before moving the mouse to travel, while others decided to travel through immediately and explore only when approaching a dead end. In this section, I will examine the individual differences in detail.

All 20 subjects were sorted from fast to slow based on their initial solving time (Fig. 3B) and this order served as the subject index. The same four-phases area plots (Figs. 7-9) were re-generated as a function of the subject index (Fig. 17 for training trials, and Fig. 18 for testing trials in the three different spatial conditions). The plots from training trials (Fig. 17) show that the time spent on early exploration and the time spent off the path varied a lot among subjects (light red band). Time spent on late exploration increased slightly as a function of the subject index. The time spent on the correct path was relative uniform across the subjects. The data from testing trials revealed the same pattern.

In order to further examine individual differences, Fig. 19 plots time in each phase as a function of the maze difficulty index (left) and the subject index (right). All measures increased as a function of the maze difficulty. The slopes were steepest for on path time and late exploration. In terms of individual differences, all measures increased as the subject index increased; the early exploration increased most. Note that there were huge individual differences in off-path time and early exploration. Compared to the on-path guidance and the late exploration, the early exploration and the off-path guidance varied a lot with the subject index. Early exploration was also correlated with error (off-path time). The more time in early exploration, the less time was spent on the wrong path. Fig. 20 is the scatter plot of early exploration vs off path time. These are negatively correlated ($R= -.56$, $p = .01$), suggesting that when subjects decided to conduct early exploration, they avoided making errors. As a reference, the correlation was also examined between the early exploration and errors of each maze in Fig. 21. There was no significant correlation between these two ($R = .147$, $p=.264$). The early exploration might not have helped to reduce the total time, namely, the occurrence of early exploration did not necessarily lead to fast maze solving. However, there was a consistent trend among individuals that people would choose to spend time either on exploration or on off-path guidance.

2.3. Discussion

There were two main goals for Experiment 1. The first was to understand the strategies people use to solve the maze, which involves how they coordinate their hand and eye movements, as well as how they manage their cognitive resources. The second was to examine the learning, specifically, whether and how much information remembered from the training maze could be transferred to the test maze.

Two phases of eye-hand coordination were found during maze solving, termed Exploration and Guidance. The time spent in each of these two phases increased as the maze difficulty increased. Guidance was stereotyped: the eye jumped ahead and the mouse caught up. Exploration seemed to vary a lot since it was an option. When solving the maze, subjects had to make continual decisions about how to divide time between these two phases.

The comparison between training trials and the testing trials, and the fact that the Expected group conduct significantly more exploration in training trials and made fewer errors in testing trials, showed that the benefits (or costs) of learning were transferred from training trials to testing. The learning affected the speed of maze traveling and the time devoted to errors in the testing trials.

Exploration was assumed to be a way to avoid mistakes in maze solving. This was confirmed by finding that exploration, especially early exploration, helped to reduce the errors (off-path guidance) when traveling in the maze. The negative correlation between early exploration and off-path guidance suggests that not exploring enough could result in more travel down the dead ends.

Early exploration varied a lot among different subjects and was negatively correlated with errors made by individual subjects. This suggests that subjects traded off time between early exploration and errors – they either spent time on early exploration and avoid errors, or saved time on early exploration and made more errors.

However, lots of trials showed no early exploration. The question raised here is this: why don't people explore more? Why subjects do still make any mistakes if it was easy to avoid mistakes by exploring? The results showed that early exploration was time consuming – subjects needed to explore about three times more time to avoid traveling to the incorrect path. It is possible that Exploration was slower and more difficult than anticipated because of the memory load. It is also possible that it may be difficult to switch between the two modes, which requires constant decision-making and planning ahead to decide if the mouse is on the correct path. So it might be much easier to just keep trying to find the route. In order to better examine the benefit of Exploration, the Experiment 2 was performed.

3. Experiment 2 (Preview condition)

Experiment 1 suggested that exploration was helpful for staying on the correct path, but it took a lot of time. Experiment 2 further examines the benefit of exploration. Experiment 2 was conducted to address the question, would exploration help learn the maze when a period of exploration was required.

3.1. Methods

3.1.1. Subjects, stimuli and eye movements

Five subjects were tested. Three were undergraduates recruited from the General Psychology subject pool who earned course credits and two were paid volunteers. All subjects had normal vision and were naive as to the purpose of the experiments. The procedures were all approved by of the Rutgers University Institutional Review Board for the Protection of human subjects. Stimuli and eye movement were the same as in Experiment 1. None of the subjects tested participated in Experiment 1.

3.1.2. Procedure

The procedure was similar to the Expected group as in the Experiment I. The only difference was that the mazes in training trials were presented for 20 s (a Preview) and subjects could freely scan the maze, but were not allowed to solve the maze using the mouse.

3.2. Results

Fig. 22 shows how time was apportioned among the three patterns in the testing trials for the Preview group. It shows that the total solving time and on-path guidance time increased as the maze difficulty increased. Less time was spent in exploration than found for the Expected group and the Unexpected group from Experiment 1in both forward and backward conditions.

The main effects of spatial relationships in the testing trials can be seen in Fig. 23, which shows the mean times spent in each phase ("On-Path Guidance" – 1^{st}, "Off-Path Guidance" – 2^{nd}, "Late Exploration" – 3^{rd}, and "Early Exploration" – 4^{th}). Fig. 10 showed the same data for Expected and Unexpected groups. Fig. 23 only includes data from the Experiment 1 Expected group (in lighter color) for comparison with the Experiment 2 Preview group (in darker color). Time spent in all phases was less for the Preview group, with the differences largest for the "early exploration" phase.

Two-way ANOVAS were conducted to compare the mean times in different phases in testing trials (see table A-5 for details). The two factors examined in ANOVA test were: (1) group (Expected vs. Preview); (2) spatial conditions (forward, backward and rotated). F-test shows that there were significant differences for all phases among different spatial conditions and for Early Exploration between two groups (see Table A-5 for details). No significant difference was found for On-path guidance, Off-path guidance and Late Exploration between two groups (Expected vs. Preview).

Pair-wised comparisons were further done in all testing conditions for all phases. For off-path guidance, the time was significantly shorter in the forward condition than in the rotated condition, and it was also significantly shorter for the Preview group in the backward condition than in the rotated condition. In terms of late exploration, the Preview group spent significantly less time in the forward condition than the Expected group in the forward and the backward conditions and the Preview group in the backward and the rotated conditions. The Preview group spent significantly more time on late exploration in the rotated condition compared to the forward and the backward conditions. Finally, early exploration has huge difference between two groups and among three testing conditions. The differences between early exploration in the Preview group and in the Expected group (Experiment 1) were significant in the forward and the rotated conditions. The longest early exploration for the Preview group (in the backward condition) was still shorter than it is for the Expected group in any testing conditions.

Finding that the Preview group spent less time on exploration than the Expected group (Experiment 1) in testing and still had fewer errors (less off-path guidance) than the Expected group (Experiment 1) in testing suggests that when subjects scanned in the maze, but were not allowed to move the mouse, they learned more than when they solved the mazes in training trials of Experiment 1.

3.3. Discussion

Experiment 2 was done to examine whether the exploration, by itself, could help to learn the maze. For the "Preview" group, subjects explored for 20s in training trials. In the testing trials, this group made fewer errors, and they also spent less time exploring. This suggests that the long time spent solely in exploration doing training trials helps learn the maze and transfer the learned knowledge to testing trials. Or, perhaps learning in Experiment 1 was impaired by the need to actually move through the maze in the training trials.

4. Transitions from Guidance to Exploration

When traveling in the maze, what condition encourages people to decide to switch from guidance to exploration mode? In this section, I will use the data from Experiment 1 to analyze the transition moments from guidance to exploration.

4.1. Selection of transition moments and reference moments

A transition moment was defined as the offset of the last of 3 consecutive guidance segments followed by at least three consecutive exploration segments. There were 1547 segments that were labeled as transition moments, in which 578 cases occurred when the mouse was off the correct path, and 969 cases occurred when the mouse was on the correct path. A reference moment was defined as the offset of a guidance segment followed by another guidance segment. There were 21,462 segments that were labeled as reference moments, in which 4,236 cases occurred when the mouse was off the correct path and 17,226 cases occurred when the mouse was on the correct path. The transition from Guidance to Exploration was more likely to occur when the mouse was off the correct path (12%) than when the mouse was on the correct path (5%).

4.2. Critical locations

There are two types of conditions may affect the decision about whether to keep traveling (guidance) or to stop and explore: (1) encountering a dead end while on the wrong path; and (2) approaching a decision point, which is the intersection of two paths.

To examine the conditions at each transition moment and reference moment, the following measures were calculated and corresponding histograms were plotted: (1)

distance from the current eye location to the nearest dead end (Fig. 24a,b); (2) distance from the current mouse location to the nearest dead end (Fig. 24c,d); (3) distance from the current eye location to the nearest decision point (Fig. 25a,b); and (4) distance from the current mouse location to the nearest decision point (Fig. 25c,d). All transition moments and reference moments were separated in to two groups based on whether the mouse was on or off the correct path. The cumulative probabilities were calculated and plotted on the right side of each histogram for each situation. 50% thresholds were found given those cumulative probabilities (see Table 6 for all 50% threshold values, and Fig. 26).

Let's look at 50% threshold for the first condition: encountering dead end while on the wrong path. The distance between the eye and the nearest dead end was shorter in transition moments than reference moments when traveling on and off the correct path (Fig. 26a). The off path cases had shorter distances than the on path cases. The distance between the mouse and the nearest dead end was slightly shorter in reference moments than transition moments when traveling on and off the correct path (Fig. 26b). Again, the off-path cases had shorter distances than the on-path cases.

Now, let's look at 50% threshold for the second condition: approaching to a decision point, which is the intersection of two paths. The distance between the eye and the nearest decision point was shorter in transition moments when traveling on the correct path and longer when off the correct path than reference moments (Fig. 26c). These distances increased from on path cases to off path cases for transition moments, and decreased for reference moments. The similar pattern was found for the distance between the mouse and the nearest decision point (Fig. 26d)

The above results descriptively show how the characteristics of the transition moments (from guidance to exploration moments) differ from those for the reference moments (from guidance to guidance segments). Given the difference between these two types of moments, the dead end and the decision point could be regarded as two of key factors that would affect subjects' decision about when should to explore again when traveling in the mazes. Finding out these factors could provide possibilities to further build up models about strategies when solving mazes.

5. Experiment 3 (Limited View condition)

Experiments 1and 2 show that exploration could help to reduce errors when solving mazes. In the Experiment 3, I will further examine the efficiency of the Exploration. The question here I want to ask is: how large is the view window that Exploration could efficiently cover.

5.1. Methods

5.1.1. Subjects

Five subjects were tested. All of them were paid volunteers. All subjects had normal vision and were naive as to the purpose of the experiments. The procedures were all approved by of the Rutgers University Institutional Review Board for the Protection of human subjects. Stimuli and eye movement were the same as in Expts 1 and 2.

5.1.2. Stimuli

The same stimuli (12*12 units mazes) were used in the limited view experiment as in Experiments 1-3. There only difference was that subjects were not always able to see the whole maze. Their view was limited in a square window surrounded the mouse position. There were five levels of window size from the mouse cursor center: 30, 60, 100, 200 and 600 pixels on a side (Fig. 27). The size of the whole maze was 600 pixels by 600 pixels and the width of path was about 60 pixels (1 pixel equals to 1 minute of arc). So subjects could see the whole maze through the largest window (600 pixels), and the smallest view window was about the same as the width of one path.

5.1.3. Procedure

The procedure was similar to previous experiments, except for two main differences.

First, subjects just needed to solve every maze one time. Each block contained 20 different mazes and subjects solved 60 mazes in total by finishing 3 blocks.

Second, subjects could only see a proportion of the maze in each trial. There were 5 levels of visible range size, from the smallest window, which was about the same width as one single path, to the largest window, which covered the full screen. Levels of visible window were randomly assigned to every trial in the experiment.

5.2. Results

Average solving time (± 1 SE) for each level of visible window size was shown in order from smallest window size to the full screen in Fig. 28. The average solving time decreased (from about 55s to about 18s) as the visible window size increased, which is the same as what we expected. As the window size decreased, the variability of subjects' performance also increased. Note that the decreasing tendency of the travel time is steep from the smallest window to the mediate window (100 level), and shallow from the mediate window to the full screen. It suggests that when the visible window is very small, any extra information added would efficiently improve the performance. While when the visible window reaches a certain level (e.g. 100 pixels as shown in the figure), more visible information would not play the same crucial role in solving mazes as it is in the smaller window. It confirms that there is an efficient size existing for exploring and integrating information when solving mazes.

Fig. 29 plots the average mouse travel length (blue), the average saccade length (red) and the average length of the correct path (black) as a function of the visible window size. With the small window sizes, the mouse travel length was much longer than the length of the correct path. Fig. 29b compares the mouse travel length and the length of correct path. As the window size increased, the mouse travel length was decreased, and reached the lower asymptote at 200 size level. It shows that the limited view increased the errors (travel to the wrong path). As the visible window size increased, the errors were reduced. Once the visible window size reached a certain level (200 pixels), such benefits were not be further increased. Fig. 29c compares the total saccade length and the length of correct path. As the window size increased, the total saccade length decreased. When the visible window size was large enough (100-600), the saccade length was even shorter than the correct path. It suggests that when the visible range was large enough, the process of gathering information by eye was very efficient that people did not need to scan all spans along the correct path. Compared to the mouse travel length, the saccade length was about the same range as the correct path (Fig. 29a). The mouse travel length was much longer and had larger variance, especially for the small windows.

Fig. 30 shows how the total maze solving time was apportioned among the 4 phases: on-path guidance (green), off-path guidance (blue), late exploration (dark red) and early exploration (light red) as a function of the maze difficulty order (see Fig. 3). Five plots represent five levels of visible window size. It shows that as the window size increased, the time spent on off-path guidance and on-path guidance was decreased, and the time spent in late exploration was increased. It seems that subjects did not conduct early exploration as frequently as in Expt 1 and 2. It supports the view that the window size could reduce errors. It also shows that the visible window size might affect the strategies by changing eye-hand coordination patterns.

5.3. Discussion

Experiment 3 was done to further examine the efficiency of exploration by varying the visible window size around the mouse. It shows that there is a limit on the benefit of the visible window size. In other words, as the visible window size increases, the maze solving performance does not always increase efficiently. Instead, the performance approaches asymptotes when the window size reaches a certain level. However, the visible window size is a crucial factor in maze solving. It affects the use of different strategies by changing the combination of eye-hand coordination patterns.

6. General Discussion

Two experiments were done in order to examine the strategies people used during a challenging visual-motor navigation task, mazes solving, and further to disclose links between eye movements and related cognitive processes, such as memory and decision making. Maze-solving makes demands on vision, attention and memory. By tracking eye and mouse movements, the strategies people use and how people learn can be inferred. The main findings can be divided into two main aspects: how eye-hand coordination links to the corresponding strategies, and the effects of learning. In this section, I will first summarize the main findings. Then, I will discuss the benefit of exploration and the link between maze-solving task and underlying cognitive processes. Finally, I will mention the possible applications and some further directions.

In Experiment 1, subjects solved mazes with or without being told they would be presented with the same maze in the next trial. One of the main findings of this experiment is the emergence of two patterns of eye-hand coordination, termed guidance and exploration. In the exploration mode, the mouse was relatively stationary and the eye jumped around to explore for information. In the guidance mode, the mouse was in motion. Typically, the eye jumped ahead and the mouse caught up. The time spent in the two modes (exploration or guidance) reveals aspects of the strategies subjects used.

Specifically, there was a trade-off between the two modes. More exploration tended to reduce the errors, which would be reflected as more “exploration” time and less “off-path guidance” time. Alternatively, subjects could explore less, spent more time on errors, but minimized the use of memory. The adjustment of strategies may depend on many factors, such as the difficulty of mazes, the spatial relationships between training and testing mazes, expectations, and subject individual differences.

Maze difficulty affected the patterns of eye-hand coordination. The total travel time increased with the maze difficulty. On-path guidance and the exploration time increased with the maze difficulty, while the off-path guidance remained similar across the difficulty range. The increased on-path guidance could be due to either the longer path, or to slower mouse travel speed, in difficult mazes. The increased exploration time suggests that the maze difficulty might also affect the decision of whether and how long to explore.

The strategies used in the maze-solving task also showed large individual differences. Early exploration was negatively correlated with the off-path guidance along the subject index (Figs. 19, 20). This suggests that people choose to trade off time between early exploration and errors during travel – either devoting time to early exploration and avoiding errors, or saving time on early exploration and spending more time on errors.

The effects of learning was studied by examine performance in testing trials. The learning effect studied here was about whether the knowledge of the maze could be transferred from the training trials to the following testing trials. Note, the learning effect here is not the “long-term” learning over time from the beginning of the experiment to the end, which could cause the adjustment of the strategies. Learning was shown by the fact that the testing trials had shorter solving times than the training trials in both the forward (the tested maze was exactly the same as the trained maze) and backward (the start and the end locations were switched in the tested maze) conditions. Learning was also evident in the rotated condition, where the training maze was rotated 180 degrees and the start and the end locations remained the same on the screen. In the rotated condition, the performance was much poorer in testing mazes. Perhaps in the rotated condition, subjects expected to apply the paths expected from the training mazes to the testing mazes, but these failed because the configuration had changed due to the rotation. Another indication of learning was that the Expected group was found to have more exploration during training trials and fewer errors (off-path guidance) in testing trials than the Unexpected group. Unexpected subjects spent less time on exploration, especially early exploration. This suggests that the benefit of exploration could be transferred to the later trial.

Experiment 2 (Preview) required subjects to explore the mazes for 20 s in the training trials without moving the mouse. The results showed that learning the mazes did not require that the maze be traveled using the mouse. The results again provided evidence of the transfer of the benefit of exploration to the testing trials, in that the Preview subjects made many fewer errors, and at the same time explored much less. This shows that people could find and remember the paths with very little actual practice or exposure.

In order to better understand strategies that encourage people to switch from guidance mode to exploration modes while traveling in the maze, two types of segments (fixation pauses) were identified – the transition segments (guidance to exploration) and the reference segments (guidance to guidance). The descriptive results show that the transition was more likely to occur when the mouse was traveling off the correct path (12%) than when the mouse was traveling on the correct path (5%). In terms of the distance from the eye or the mouse to the nearest dead end or the nearest decision point, the transition moments also differed from the reference moments when encountering dead end while on the wrong path and approaching a decision point, which is the intersection of two paths. Subjects were more likely to switch from guidance to exploration when the eye getting near to a dead end. These differences could be further used when modeling strategies in maze-solving task.

Experiment 3 (the limited view window) shows that there is an efficient window size. The performance increased a lot (maze solving time reduced) as the visible window size increased from tiny visible range to medium range. However, the performance could not efficiently increase when the visible window size is larger than this efficient size. The size of efficient visible range reflects the radius range that people could explore and integrate information from peripheral vision. The efficient visible range might vary among different individuals and affect the use of strategies. Thus, it could be treated as an important factor when modeling the maze solving strategies.

6.1. Why not explore more to avoid errors?

There is a critical decision subjects need to make while solving mazes, namely, whether to try to keep moving as fast as possible in the maze at a risk of error, or to stop moving and rely on exploration with the eye to find the correct paths. Errors (travel on the wrong path) are time-consuming because people have to back-track, while exploring would seem to be less time-consuming, since saccades are so fast. It would see that in order to achieve the best performance in maze solving, people should use the eye to explore the mazes and not have any errors at all (not travel on wrong path). The data shows people did explore, and exploring was helpful in that people who spent more time on exploration usually had fewer errors in the testing trials, especially when people knew the maze would be repeated and forced to explore the maze. The time spent on off-path guidance was also shown as negatively correlated with the exploration.

However, there were still a proportion of subjects who chose to travel with the mouse immediately and learn from errors, rather than exploring to gather information (see Figs. 17, 18). But others did not explore and spent more time on the wrong path. This suggests that some did not explore enough, or there are limits in the value of explorations. The question raises here: Why don't people explore more? Why do they choose to make mistakes, if these mistakes could be easily avoided?

The correlation analysis (Figs. 14 & 20) shows that the exploration, especially the early exploration, was negatively correlated with the off-path guidance. However, as showed in Fig. 14, exploration did not help to save time. In general, in order to reduce off-path guidance, subjects needed to spend three times of time on exploration. The choice of trade-off between exploration and guidance varied a lot among different people. When examining the correlation between early exploration and the off-path guidance for each subject, I found that subjects were making decisions on spending time either on exploration and avoid errors, or on learning from errors but not exploring (Figs. 19, 20).

There might be two possibilities that could explain why exploration would not be helpful? One possibility is that, exploration might be more difficult than we think because there is a memory load. People might prefer to directly react to obvious situation, rather than dealing with a memory load. But, given the facts that people were able to learn the mazes in the Preview group and further reduced errors, it might still not reach the memory limits when people relied on exploration to solve the maze. The limits in the value of exploration were not due to the total absence of memory since the results showed that considerable learning occurred. But the cost in time or effort of using memory might discourage people from conducting more explorations. The other possibility is that, it may be difficult to switch between the two modes: guidance and exploration. The switch process may require more efforts, such as planning. This "lazy" pattern was also found in previous studies, such as block-stacking task (Flanagan and Johansson, 2003) where they found subjects' gaze landed at the target slightly before the hand, and block-copying task (Ballard, Hayhoe and Pelz, 1995) where they mentioned people use a "just-in-time" strategy. Both of these two studies provided evidence that people might avoid planning ahead if immediately reacting to situations was sufficient to solve problems. There is constant decision-making and planning ahead to decide if you are on the correct path. So, it may be much easier to just keep trying until you find the route. Instead of planning the whole path in a head by exploration which requires much computation, in order to make the process efficient, people might choose to explore for a certain amount of information that is just enough for the next few steps, and then update the knowledge of the maze when traveling.

6.2. What is an optimal strategy for solving mazes?

If people did not explore enough, and since I assume people are using a good strategy, an optimization computation must be involved. What are people optimizing? Previous work discussed several possible optimization strategies. For example, the optimization could be minimize the use of the internal memory, and using the “world” as external memory. Subjects scan to get the information just before using it, instead of scanning and planning in advance and keeping all information in memory (Ballard, et. al., 1995). Epelboim and Suppes (2001) pointed out that people use their visual working memory up to its capacity (how many items are able to be stored), which can be filled quickly at the beginning of problem solving, and then use the eye to scan new information or rescan old information to overwrite the stored information. In another words, people solve problems step-by-step by updating the memory step-by-step, instead of planning ahead for the whole solution.

The maze solving task is different from those previous studies because in this task, the cost of errors (travel on the wrong path) exists. Thus, failure to explore and use memory has more negative consequences and would significantly increase the solving time more than in the tasks such as block-copying (Ballard, et al., 1995), block-stacking (Flanagan & Johansson, 2003), or solving the traveling salesman problem (Kong, et. al., 2010). Given the fact that the Preview group performed much better than the Expected group in testing trials, it suggests that with the requirement of exploration in the Preview group, subjects were able to use more memory to improve the performance in the task. So, in the regular maze solving task as in the Expected group, either people prefer to avoid the use of memory, or there is an upper bound on the benefit of using memory during performance of a motor task, perhaps because of costs of retrieval. It is also possible that the main benefits of exploration are limited to long-term (across trial) benefits, instead of immediate benefits (within trials). Thus, multiple types of memory, such as short term memory when applying the scanned information to solve the maze in the current trial, long term memory when applying the gained information to the following trial, may be involved.

In addition, when solving the maze, people might optimize different aspects. People might want to minimize the solving time, the use of memory or the number of decisions to be made, as I discussed above. People might also want to maximize the enjoyment or achievement of maze-solving "game". The optimization could also vary a lot among individuals. Thus, many cognitive factors as well as social factors should be considered when building up the related computational models about optimal and sub-optimal strategies.

6.3. Eye-movements, eye-hand coordination and underlying cognitive processes

Now, let's go back an important question raised at the beginning of the Introduction: Whether eye movements could help to reveal the underlying cognitive processes? Many studies have been done in order to address this question, as I reviewed in the Introduction. The present study can address the question at some levels, by satisfying the requirements Viviani listed. First, the maze solving task is a sequential task in which, people have to make decisions step by step based on the previously gathered information. This provides a possibility that cognitive processes could be linked to the eye movement sequence, step-by-step. Second, besides eye movements, the records of hand movements added another dimension (hand) in the way of unearthing the underlying cognitive processes. It is well known that there is a collaborative pattern between eye and hand movements, that the eye usually fixates at the target in ahead and then guides the hand to the target. For example, Ballard, Hayhoe and Pelz (1995) reported that people prefer to use “just-in-time” strategy in block-copying task, that the eye only scanned to get the corresponding information about one block at a time just before use it. Epelboim, et. al. (1997) reported that gaze-shifts help to guide the arm from one target to anther in tapping task. Flanagan et. al. (2003) reported that people usually fixated on the target slight before the index finger picking up the block in block-stacking task. However, these eye-hand coordination tasks usually were relatively easy and did not necessary involved high level cognitive processes, such as planning and memorizing the route, or making decision about which path should be chosen. Solving a maze is such a problem in which people have to rely on memory, make decisions such as taking which path, and do the task sequentially. In order to solve the maze quickly, people need to make a trade-off between scanning for more information and moving as fast as possible. So, in the experiment paradigm here, maze solving, people have to conduct some high level cognitive process, such as planning, memory and decision making, could be a good tool to study the cognitive processes through eye (and hand) movements.

6.4. Applications and Further directions

The present study tries to address the critical question about how eye movements can reveal the underlying cognitive processes, and it also raises new questions about how people devise optimal strategies for performing visual-motor tasks. The strategies people used to solve mazes involve trade-offs between memory and visual guidance and involve consideration of the cost in time or effort of making errors vs. the cost in time or effort of preventing errors. Unearthing the strategies of this type of trade-off can be valuable. With these strategies, we can understand how human process information, including: (1) what should be stored in memory; (2) when to input new information; (3) how to update the states given the new inputs and the previous components in memory; and (4) how the updates change the decisions. The strategies differ a lot among different subjects, which suggest that people might be able to be categorized into different groups and might need different assistant when doing a similar task in a natural environment.

A better understanding the mechanisms could facilitate some areas, such as AI and human-machine interaction. For example, when using a GPS or other devices for guidance during road navigation, information about individual style and capacities could determine how much information should be provided to its user, so that it would be just enough. Also, understanding human strategies of trading off exploration and guidance can inform can inform robotics algorithm that aim to let robot behave with human-like intelligence and better communicate with human beings.

However, in order to better understanding the mechanisms, there is still much work to be done, besides the findings I discussed above. First, I need to design several new experiments to find out whether the strategy each person conducted could be adjusted. If the strategy could be adjusted, whether the adjustment automatically appears as people get more familiar with the task over time, or can be controlled by providing rewards and penalties. I also need to further study the transition and find out the factors that make people decide to switch from one mode (guidance) to another (exploration). Second, given these factors, it may be possible to simulate the occurrences of these transitions. The final goal is to build up models that simulate the strategies people choose based on different parameters, such as subjects personal characteristics and maze difficulty. With accomplishments on the above directions, it will be possible that maze-solving can provide fundamental insight into human cognition and its role in real-world problem-solving.

Tables

Table 1. R scores and P values of the correlation between the proportion of time one early/late Exploration in Training trials and the proportion time on off the correct path Guidance in Training trials. Slope and Intercept of best-fitting line of the data.

		Correlation		Best-fitting line	
		R	**p**	**Slope**	**Intercept**
Expected Group	**Early Exploration Vs. Error**	-.39	<.001 ***	-.39	.17
	Late Exploration Vs. Error	.17	<.001 ***	.28	.09
Unexpected Group	**Early Exploration Vs. Error**	-.36	<.001 ***	-.47	.20
	Late Exploration Vs. Error	-.02	.678	-.03	.15

Table 2. R scores and P values of the correlation between the proportion of time on early/late Exploration in Training trials and the proportion time on off the correct path Guidance in Testing trials. Slope and Intercept of best-fitting line of the data.

		Correlation		Best-fitting line	
		R	**p**	**Slope**	**Intercept**
Expected Group	**Early Exploration Vs. Error**	-.18	<.001 ***	-.16	.13
	Late Exploration Vs. Error	-.04	.345	.05	.11
Unexpected Group	**Early Exploration Vs. Error**	-.12	.004 **	-.14	.14
	Late Exploration Vs. Error	-.11	.007 **	-.19	.14

Table 3. R scores and P values of Partial Correlation Between Exploration and Errors (Off-path Guidance)

		Correlation	
		R	p
Expected Group	Early Exploration in Training Vs. Error in Training	-.42	<.001 ***
	Late Exploration in Training Vs. Error in Training	.25	<.001 ***
	Early Exploration in Training Vs. Error in Testing	-.15	.021
	Late Exploration in Training Vs. Error in Testing	-.08	.235
	Early Exploration in Testing Vs. Error in Testing	-.32	<.001 ***
	Late Exploration in Testing Vs. Error in Testing	.19	<.001 ***
Unexpected Group	Early Exploration in Training Vs. Error in Training	-.37	<.001 ***
	Late Exploration in Training Vs. Error in Training	-.09	.092
	Early Exploration in Training Vs. Error in Testing	-.14	.013
	Late Exploration in Training Vs. Error in Testing	-.07	.211
	Early Exploration in Testing Vs. Error in Testing	-.32	<.001***
	Late Exploration in Testing Vs. Error in Testing	-.04	.373

Table 4. R scores and P values of Partial Correlation Between Exploration and On-path Guidance

		Correlation	
		R	**p**
Expected Group	**Early Exploration in Training Vs. On-path Guidance in Training**	-.22	<.001***
	Late Exploration in Training Vs. On-path Guidance in Training	-.35	<.001***
	Early Exploration in Training Vs. On-path Guidance in Testing	-.18	.009**
	Late Exploration in Training Vs. On-path Guidance in Testing	.19	.004**
	Early Exploration in Testing Vs. On-path Guidance in Testing	-.22	<.001***
	Late Exploration in Testing Vs. On-path Guidance in Testing	-.49	<.001***
Unexpected Group	**Early Exploration in Training Vs. On-path Guidance in Training**	-.10	.052
	Late Exploration in Training Vs. On-path Guidance in Training	-.37	<.001***
	Early Exploration in Training Vs. On-path Guidance in Testing	-.18	.001***
	Late Exploration in Training Vs. On-path Guidance in Testing	-.04	.454
	Early Exploration in Testing Vs. On-path Guidance in Testing	-.20	<.001***
	Late Exploration in Testing Vs. On-path Guidance in Testing	-.37	<.001***

Table 5. Normalized index into 0-1

Slope	Maze Difficulty Index	Subject Index
On path guidance	10.256	8.080
Off path guidance	1.476	3.217
Early Exploration	1.165	9.136
Late Exploration	2.098	6.327

Table 6. 50% threshold

	G to E On path	G to E Off path	G to G On path	G to G Off path
Eye to deadend	62.2	58.1	66.4	60.8
Mouse to deadend	69.4	62.9	68.1	62.0
Eye to decision point	72.7	76.8	75.1	70.6
Mouse to decision point	77	76.8	78.1	72.6

Figures

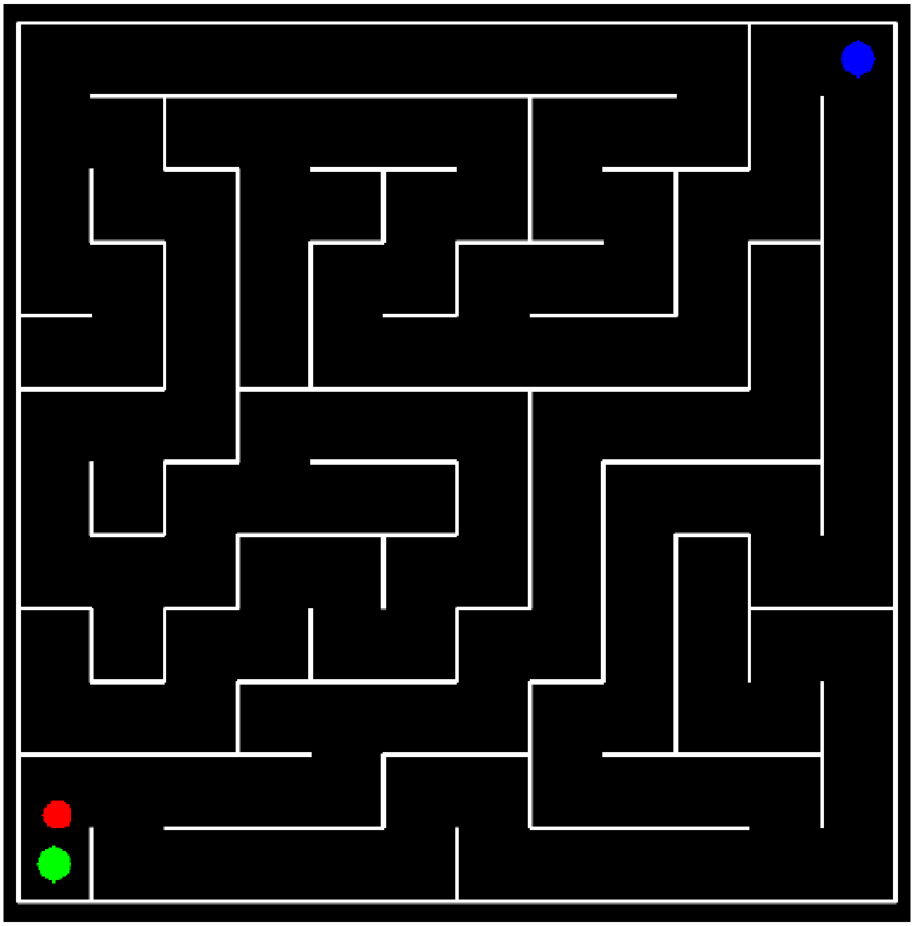
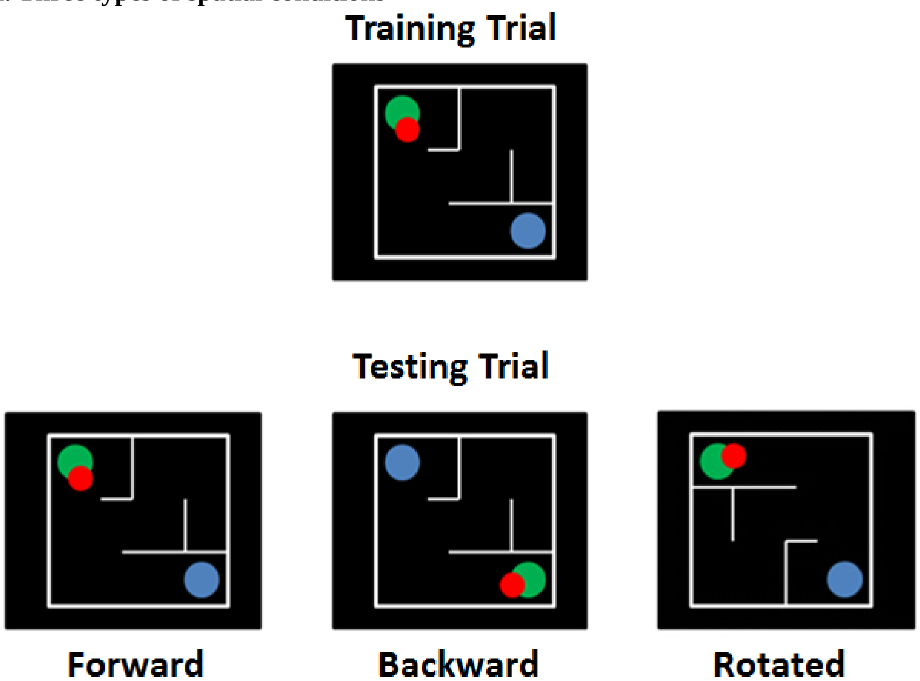


Figure 1. An example of a maze used in the experiment

a. Three types of spatial conditions



b. The procedure of a typical training trial for Expected group

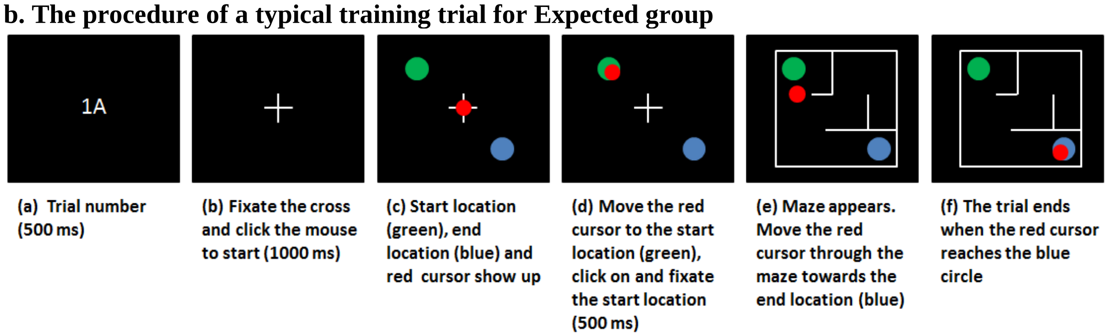
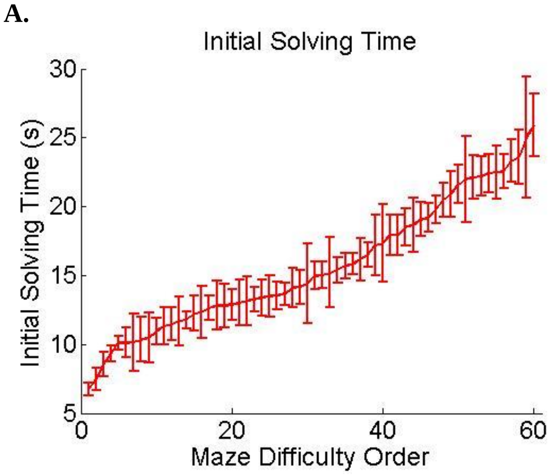


Figure 2. (a) Three types of maze spatial relationship between training trials and following testing trials. (b) The procedure of a typical training trial for Expected group.

A.



B.

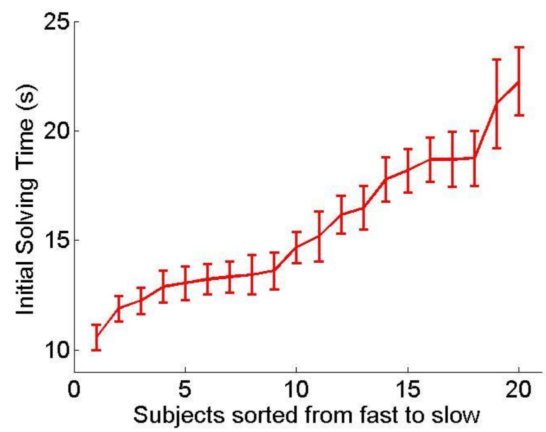


Figure 3. Initial Travel time (s). It is sorted from the shortest to longest. (A) The mean of initial solving time for each maze. (B) The mean of initial solving time for each subject (red line), sorted from fast subject to slow subject.

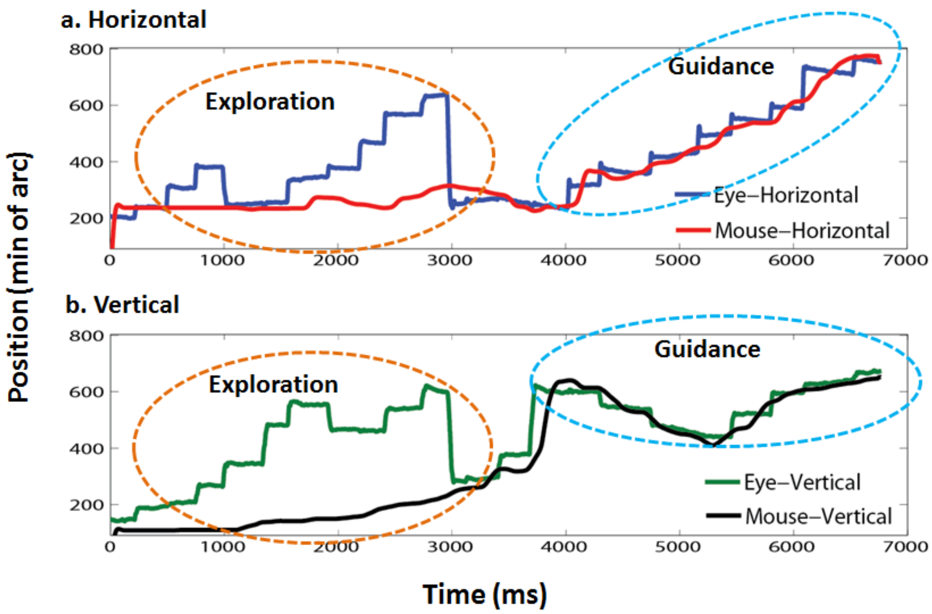


Figure 4. Example of eye and mouse traces. Eye positions (blue is horizontal direction and green is vertical direction) and mouse positions (red is horizontal direction and black is vertical direction) were plotted as a function of time.

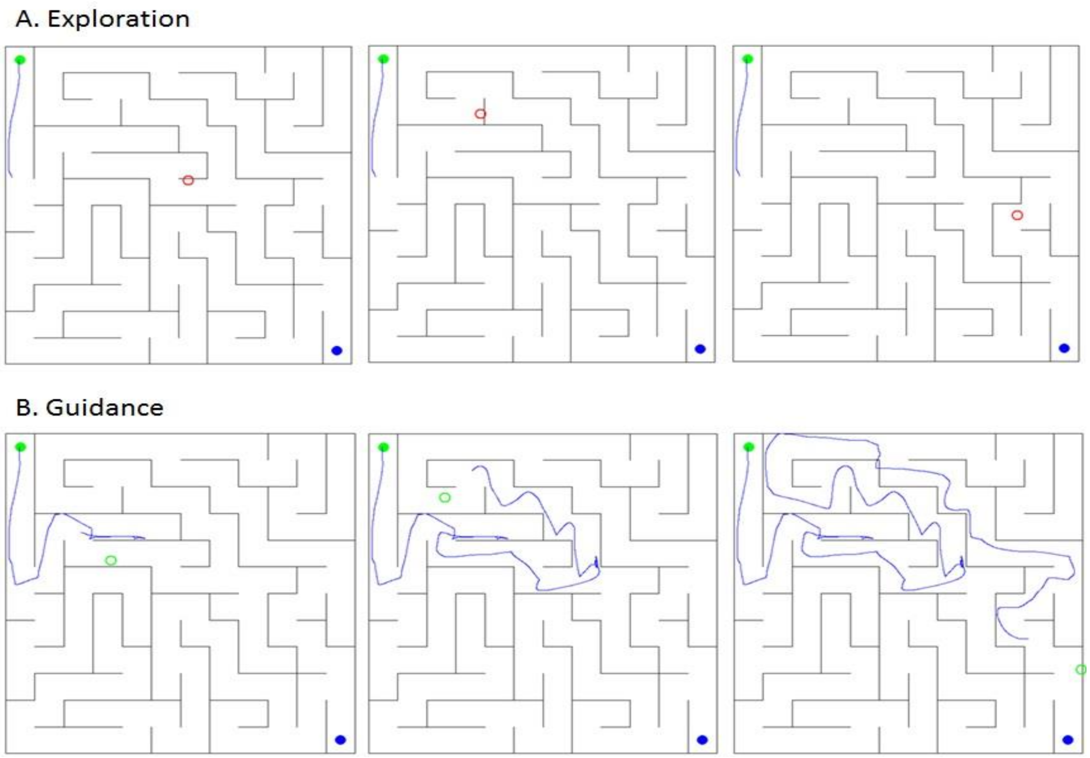


Figure 5. Selected frames from dynamic plot of eye and mouse positions in a maze solving trial. There are two main modes of eye-hand coordination (A: Exploration; B. Guidance). Offset of each saccade (circle) and mouse positions (blue line) were plotted on the maze dynamically. There were two patterns: exploration (upper plots) and guidance (lower plots). In exploration mode, mouse (blue line) stopped or slow down and eye (red circle) was sent out to explore in the maze. In guidance mode, eye (green circle) jumped ahead and waited for mouse (blue line) to catch up.

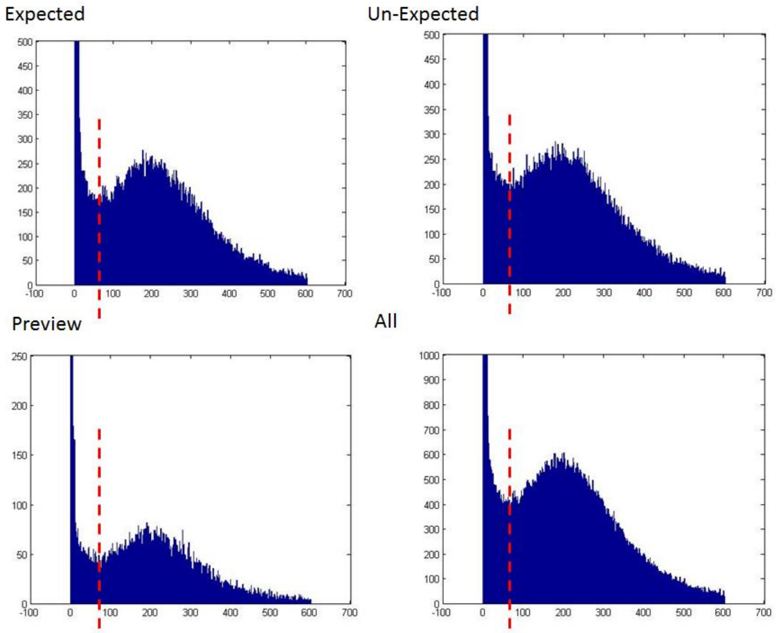
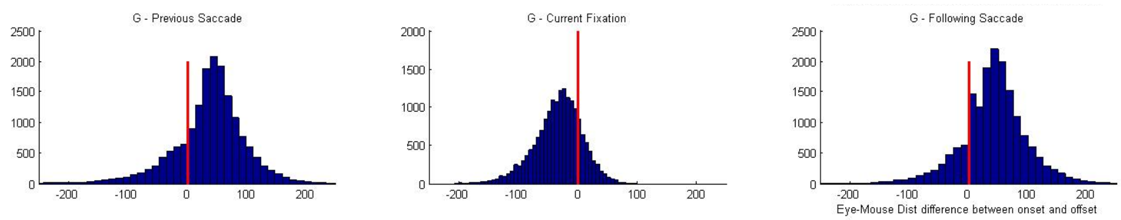


Figure 6. Density distribution of mouse speed in each segments in "Expected" group (upper left), "Un-Expected" group (upper right), Preview group (lower left, from Experiment 2) and combined all groups (lower right). Criteria (speed = 70 pixel/s, red line) of dividing guidance pattern and exploration pattern based on mouse movements speed

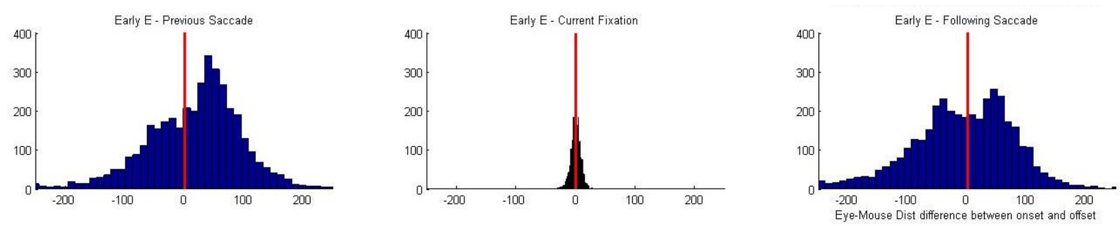
A. Guidance

a b c



B. Late Exploration

d e f



C. Early Exploration

g h i

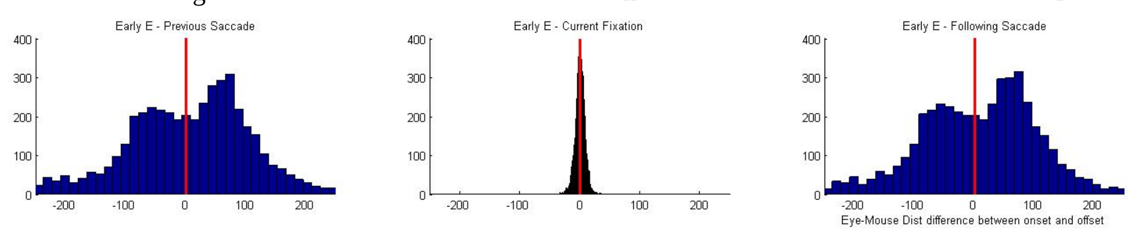


Figure 7. The difference of distances between eye and mouse at the onset and offset of fixations (middle column, b, e, h), the previous saccades (left column, a, d, g) and the following saccades (right column, c, f, i). There are three cases: guidance (upper row, a, b, c), early exploration (middle row, d, e, f) and late exploration (lower row, g, h, i).

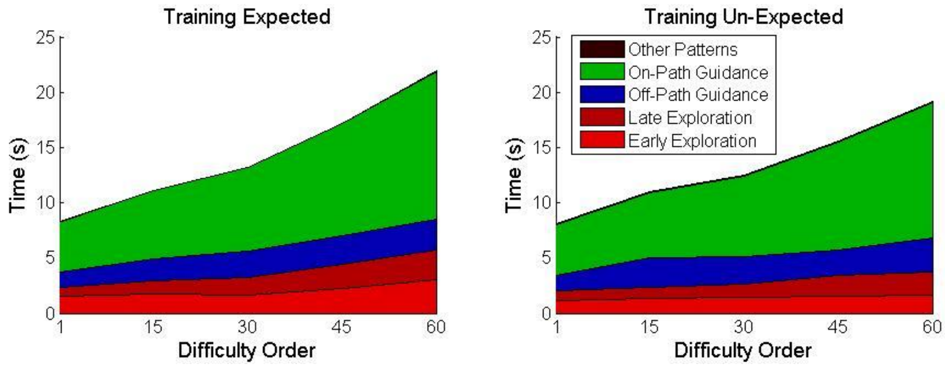


Figure 8. Times of different eye-hand coordination patterns in training trials as a function of maze difficulty order, from "Expected" group (left plot) and "Un-Expected" group (right plot). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

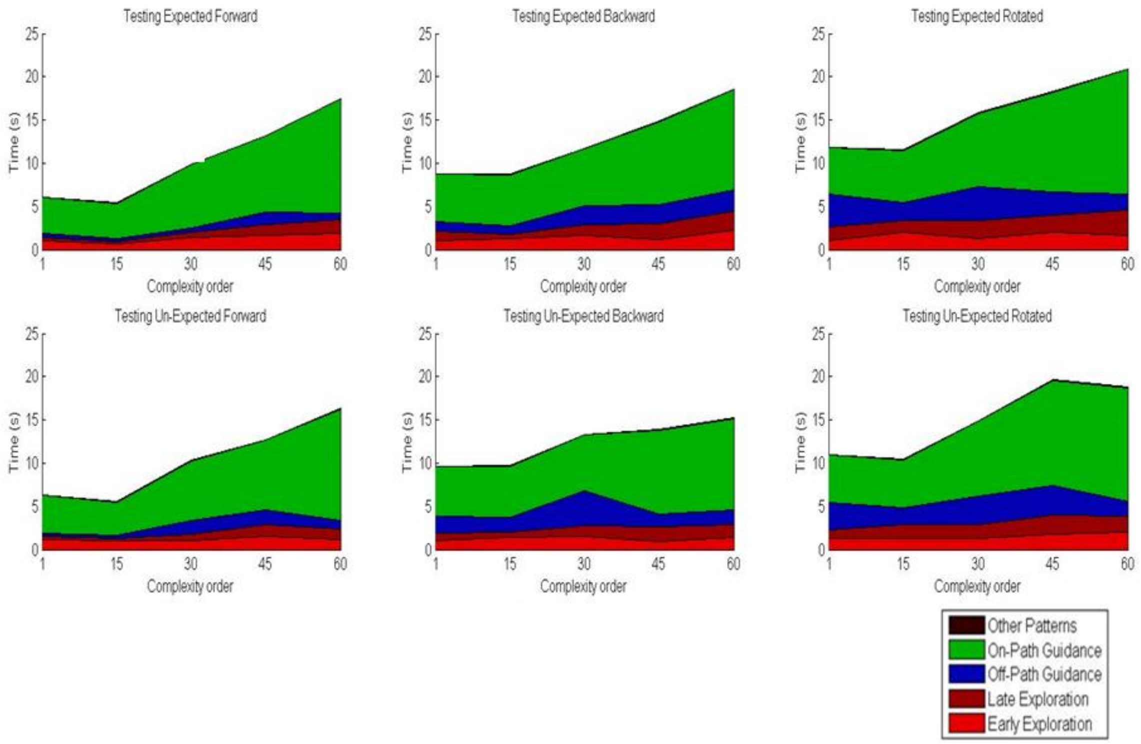


Figure 9. Times of different eye-hand coordination patterns in testing trials as a function of maze difficulty order, from "Expected" group (upper plots), "Un-Expected" group (lower plots). 60 mazes were separated based on the spatial relationships (forward – left; backward – middle; rotated – right). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

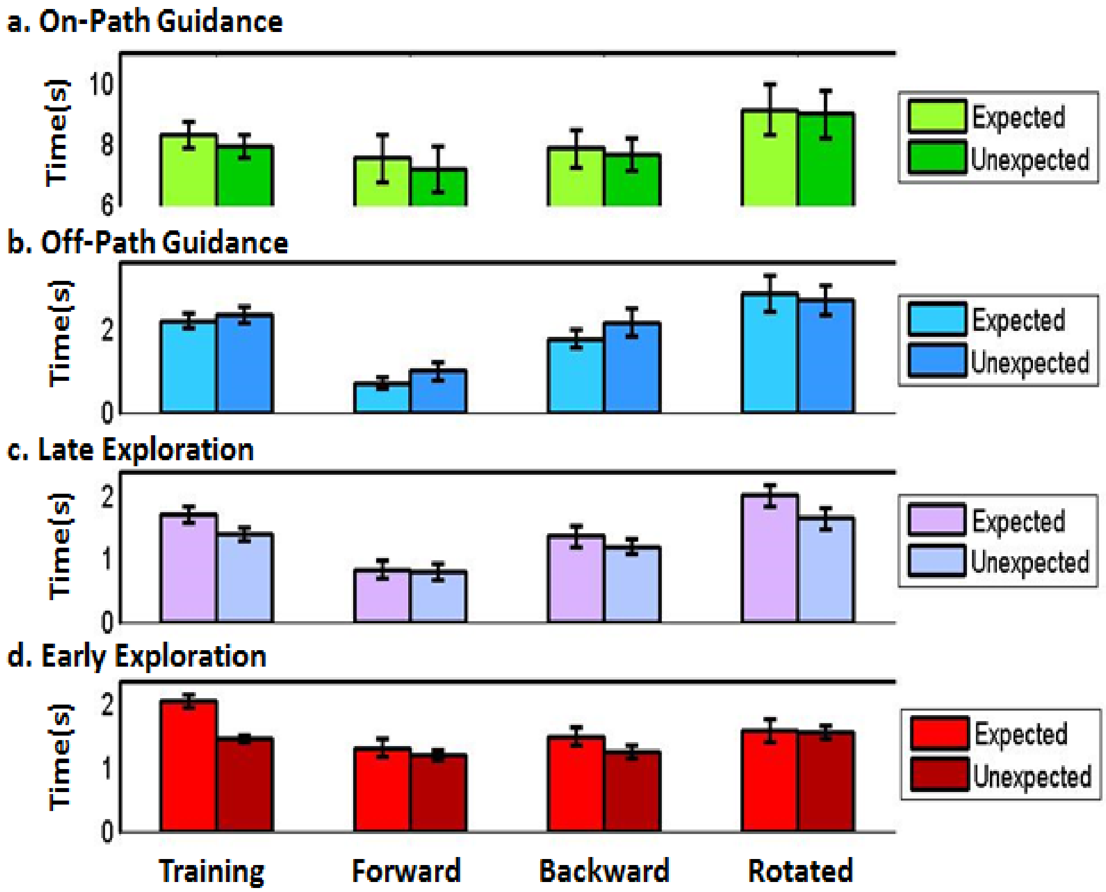


Figure 10. Mean times of different eye-hand coordination patterns in difference conditions and different groups. There were four main patterns: early exploration (red); late exploration (purple); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green). Subjects were from one of two groups: "Expected" group (in light color), "Un-Expected" group (in dark color).

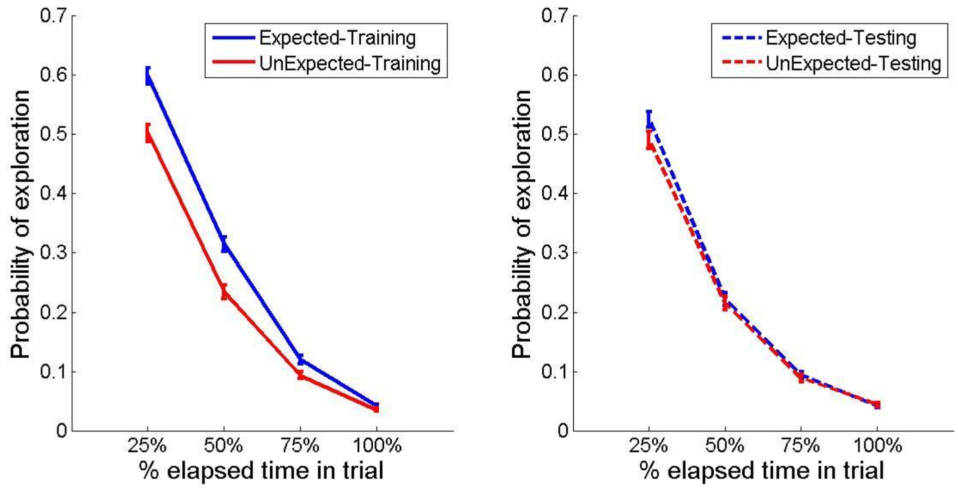


Figure 11. Probability of exploration as a function of trial time. Data are from training trials (blue lines) and testing trials (red lines). There were two groups of subjects: the Expected group (left plot) and the Unexpected group (right plot).

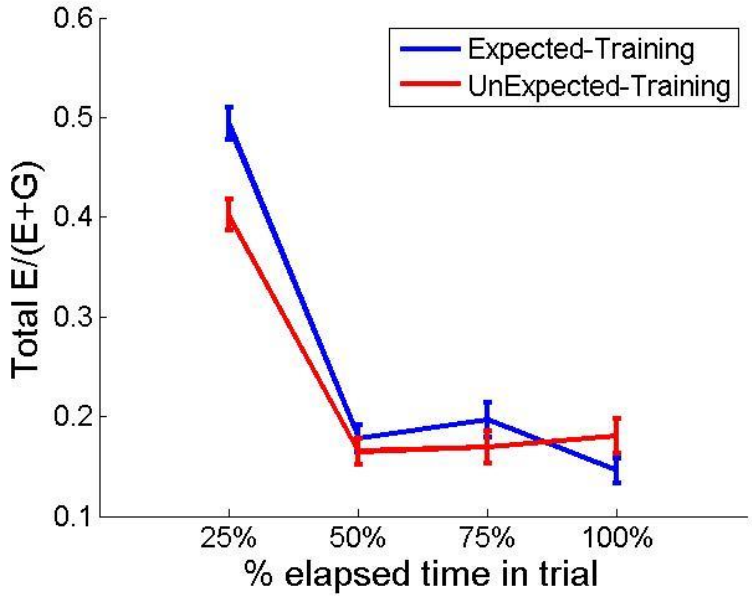


Figure 12. Ratio of time on Exploration to the total time a function of trial time. The ratio is calculated as the exploration duration divided by the sum of the exploration duration and the guidance duration.

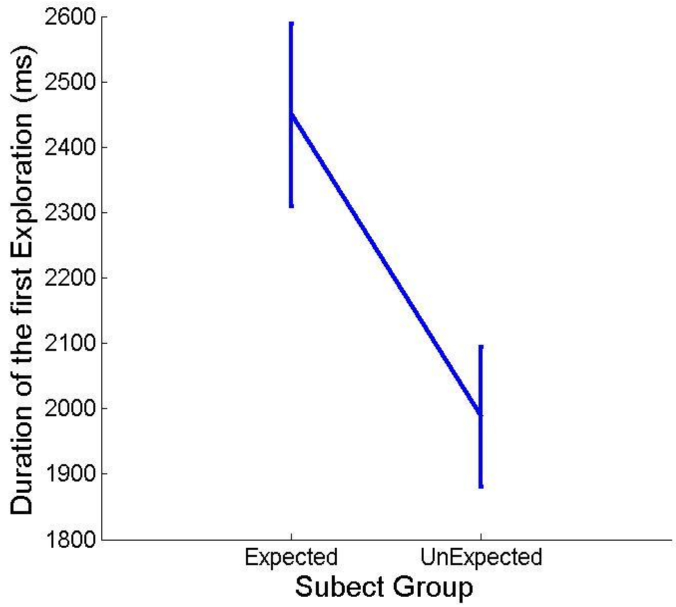


Figure 13. Average of total duration of the early Exploration in the "Expected" and the "Un-Expected" groups.

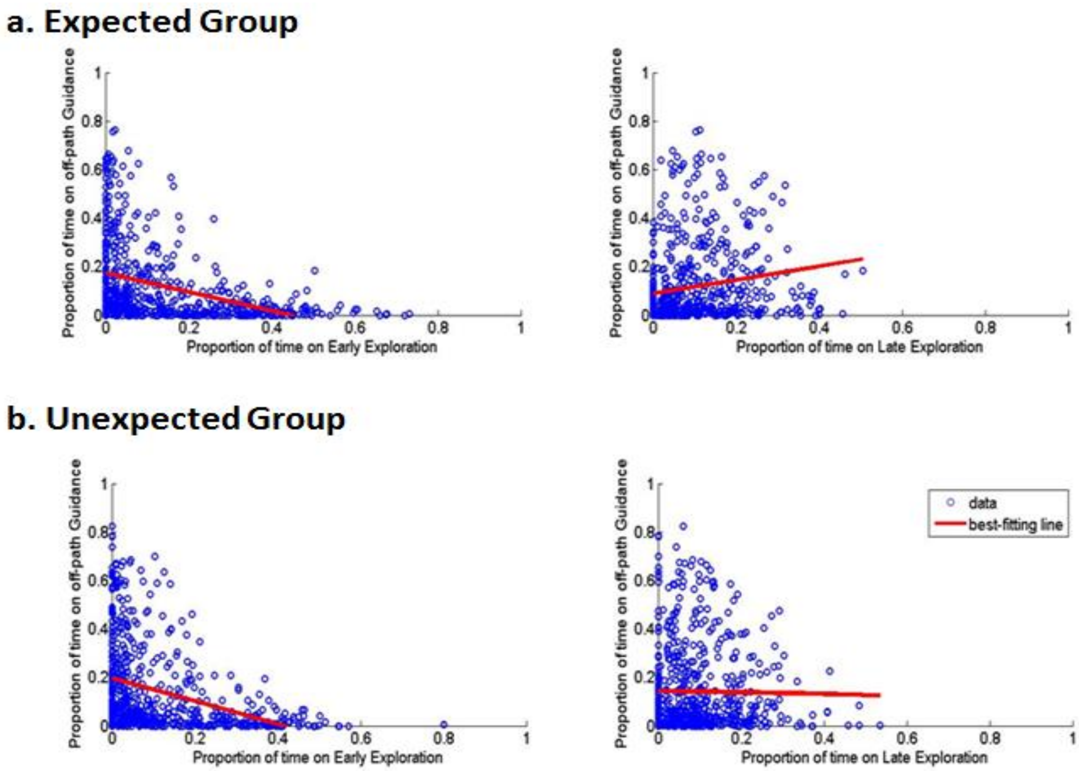


Figure 14. Scatter plot about the relationship between the proportion of time on early Exploration (left two plots) or late Exploration (right two plots) in Training trials and the proportion time spent off the correct path Guidance in Training Trials. There were two groups: the Expected group (a) and the Unexpected group (b). Blue dots are actual data, and red lines are best fitting line for these data.

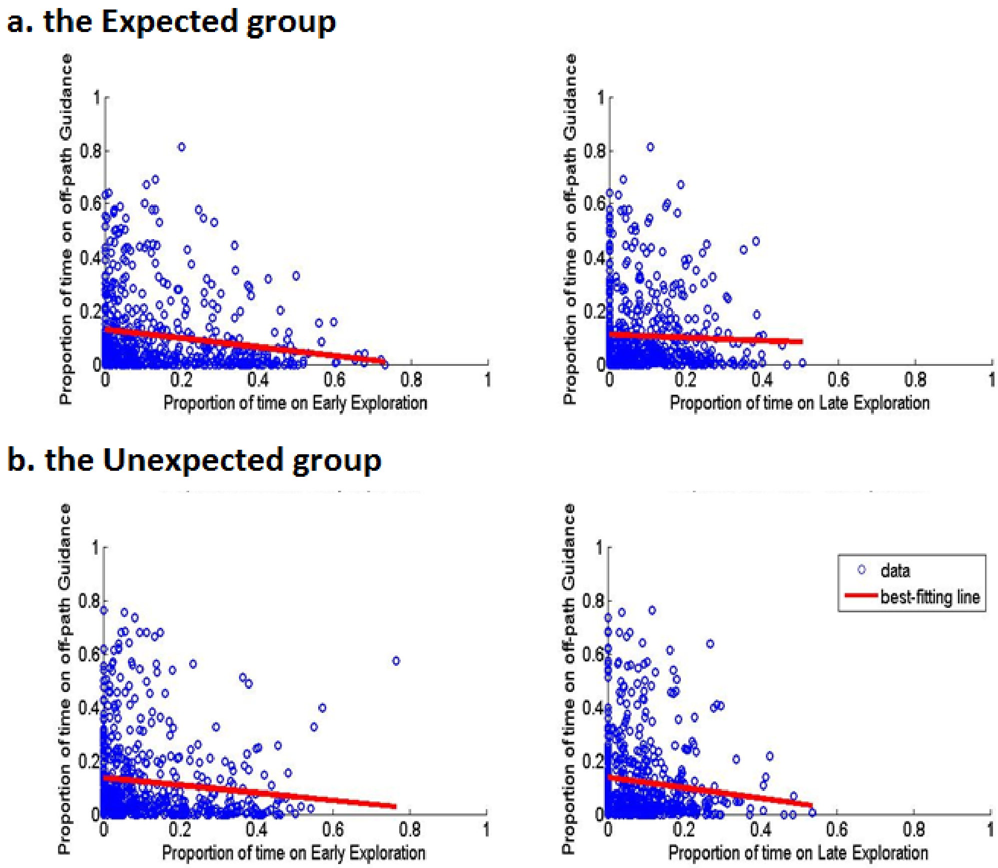


Figure 15. Scatter plot about the relationship between the proportion of time on early Exploration (left two plots) or late Exploration (right two plots) in Training trials and the proportion time on off the correct path Guidance in Testing Trials. There were two groups: the Expected group (a) and the Unexpected group (b). Blue dots are actual data, and red lines are best fitting line for these data

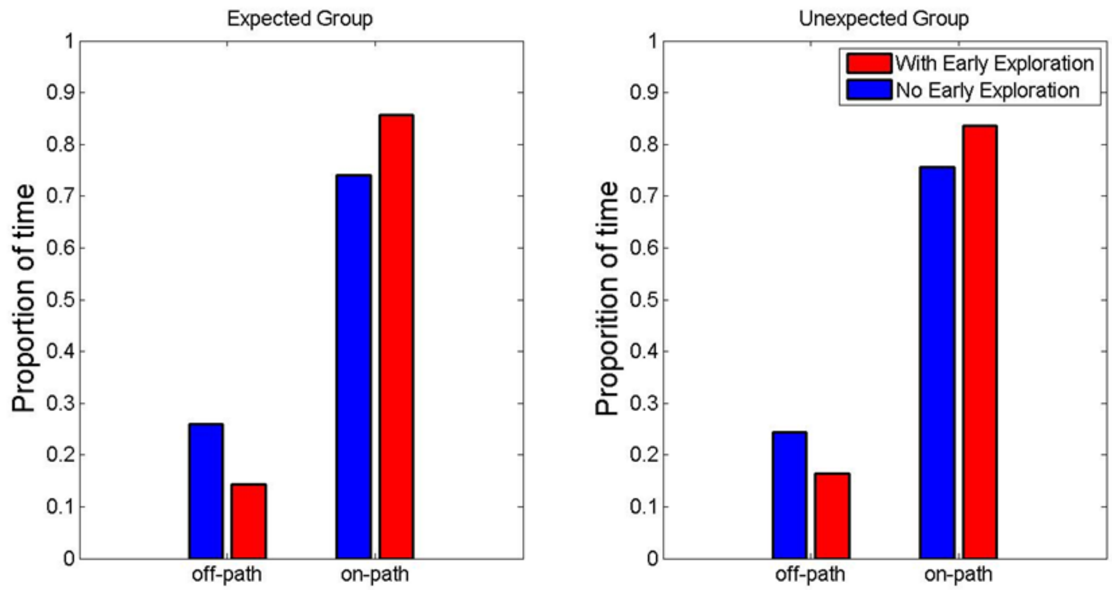


Figure 16. Proportion of time on/off the correct path in trials, with (blue bars) or without (red bars) the early Exploration. There were two groups of data: the Expected group (left plot) and the Unexpected group (right plot).

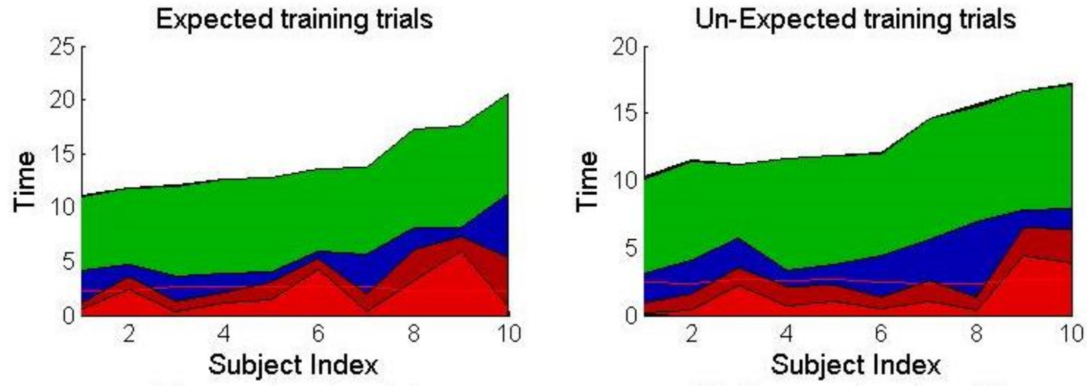


Figure 17. Times of different eye-hand coordination patterns in training trials as a function of subject index, from "Expected" group (left plot) and "Un-Expected" group (right plot). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

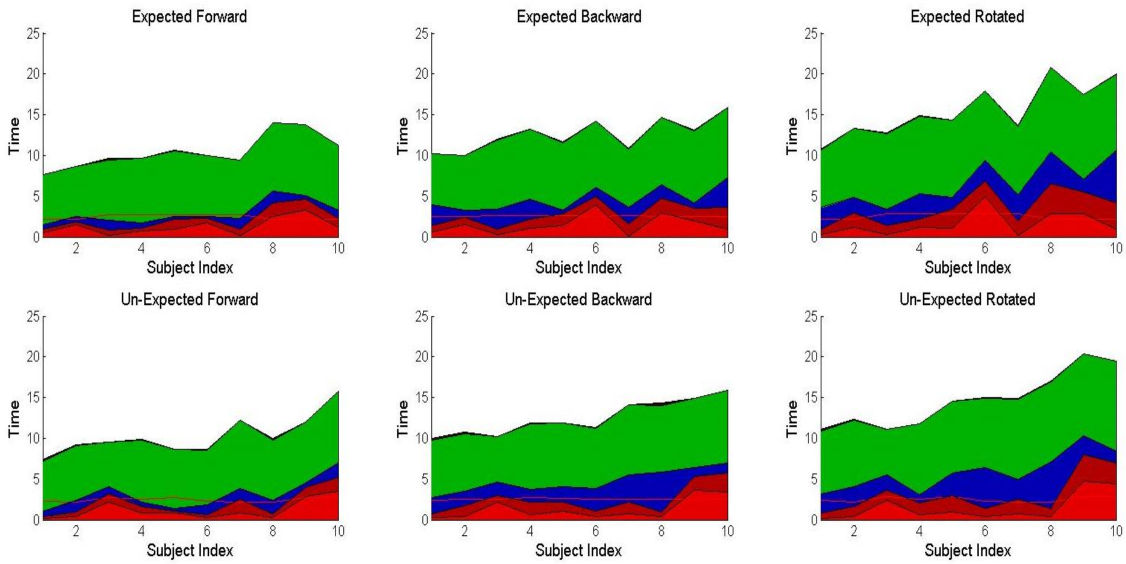


Figure 18. Times of different eye-hand coordination patterns in testing trials as a function of maze difficulty order, from "Expected" group (upper plots), "Un-Expected" group (middle plots) and Preview group (lower plots). 60 mazes were separated based on the spatial relationships (forward – left; backward – middle; rotated – right). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

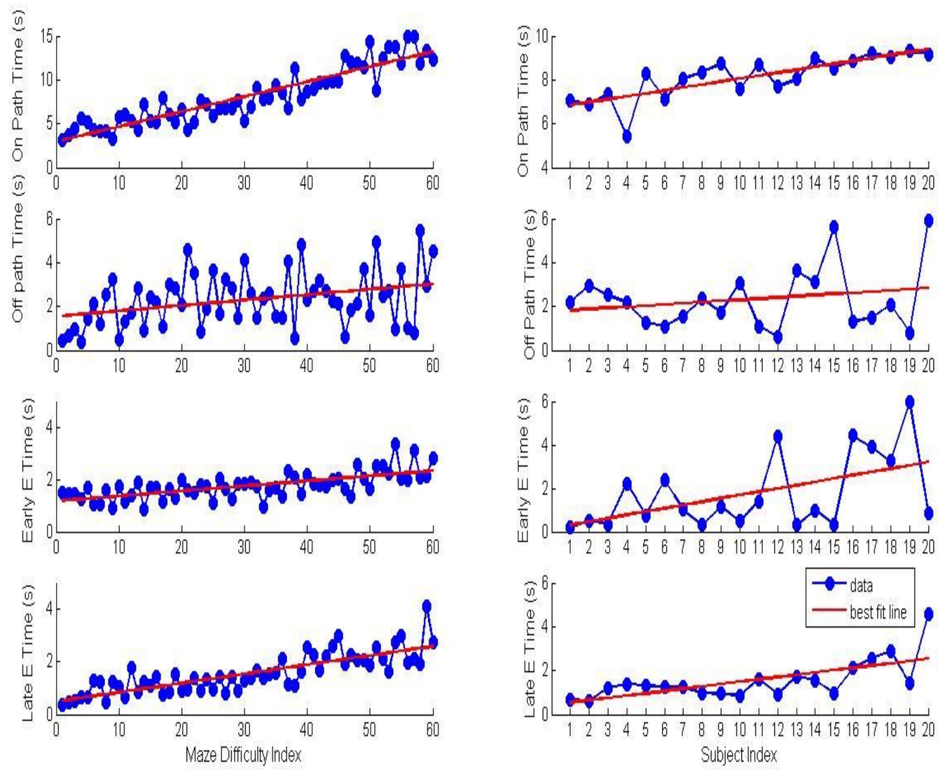


Figure 19. The time spent on four phases as a function of maze difficulty index (left plots) and subject index (right plots). Four phases are: on-path guidance (1st row); off-path guidance (2nd row); early exploration (3rd row) and late exploration (4th row).

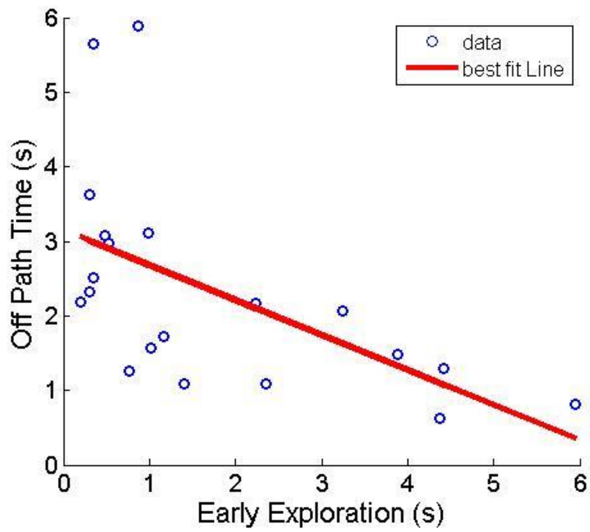


Figure 20. Scatter plot of off-path guidance time as a function of early exploration. Blue dots are data. Each dot represents a subject. Red line is the best-fit line of the data.
R-score = -.56; p = .01 ** Slope = -.469

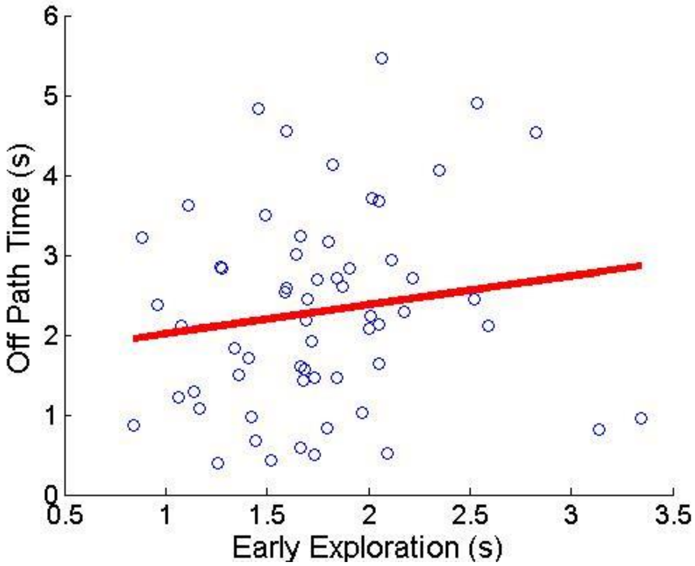


Figure 21. Scatter plot of off-path guidance time as a function of early exploration. Blue dots are data. Each dot represents a maze. Red line is the best-fit line of the data.

R-score = .147; p = .264   Slope = .36

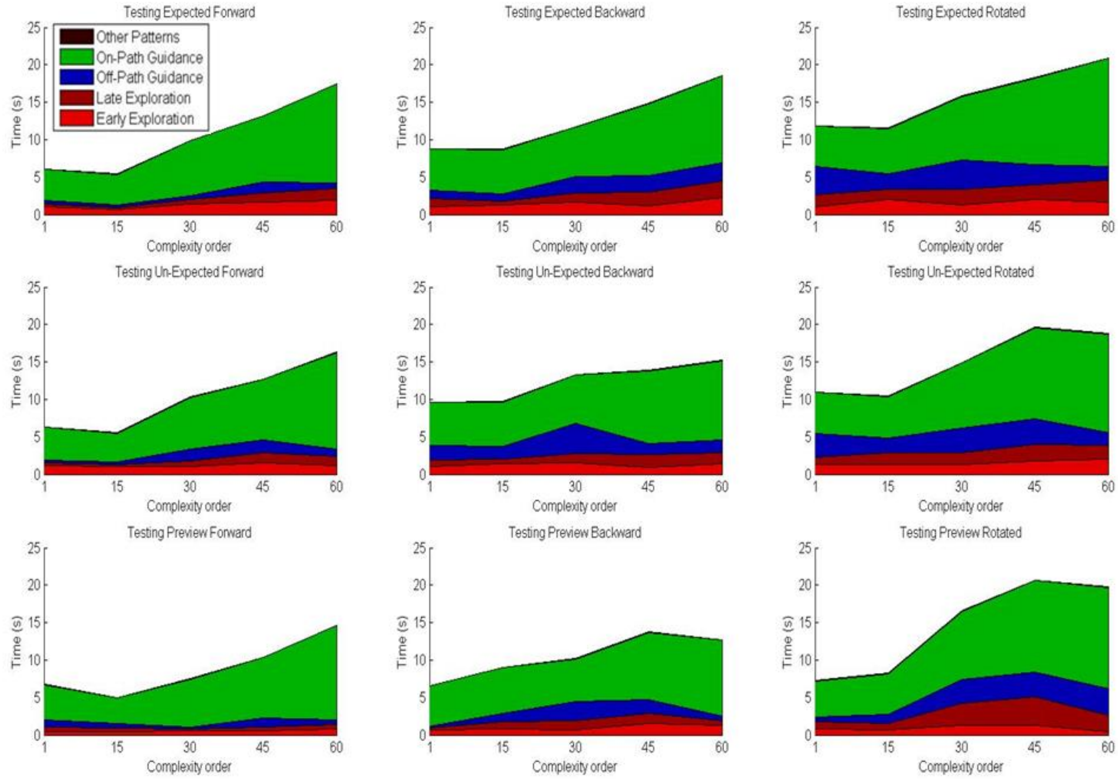


Figure 22. Times of different eye-hand coordination patterns in testing trials as a function of maze difficulty order, from "Expected" group from Experiment 1 (upper plots), "Un-Expected" group from Experiment 1 (middle plots) and Preview group from Experiment 2 (lower plots). 60 mazes were separated based on the spatial relationships (forward – left; backward – middle; rotated – right). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

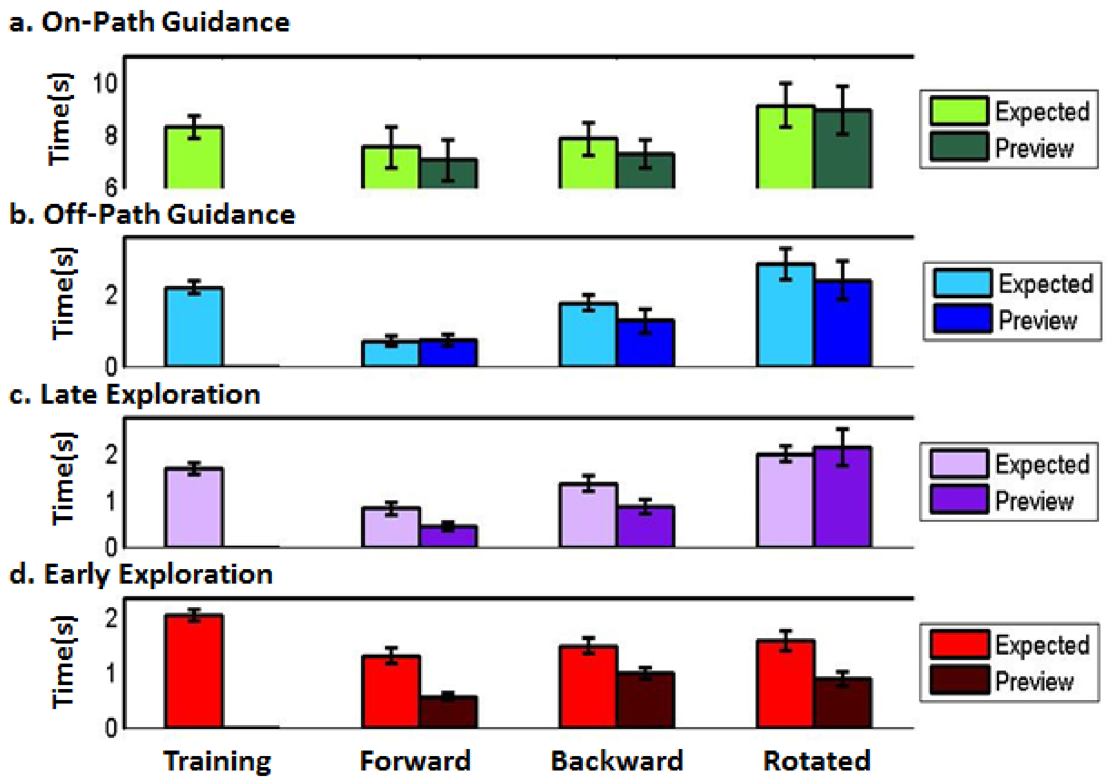


Figure 23. Mean times of different eye-hand coordination patterns in difference conditions and different groups. There were four main patterns: early exploration (red); late exploration (purple); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green). Subjects were from one of two groups: "Expected" group from Experiment 1 (in light color), "Preview" group from Experiment 2 (in dark color).

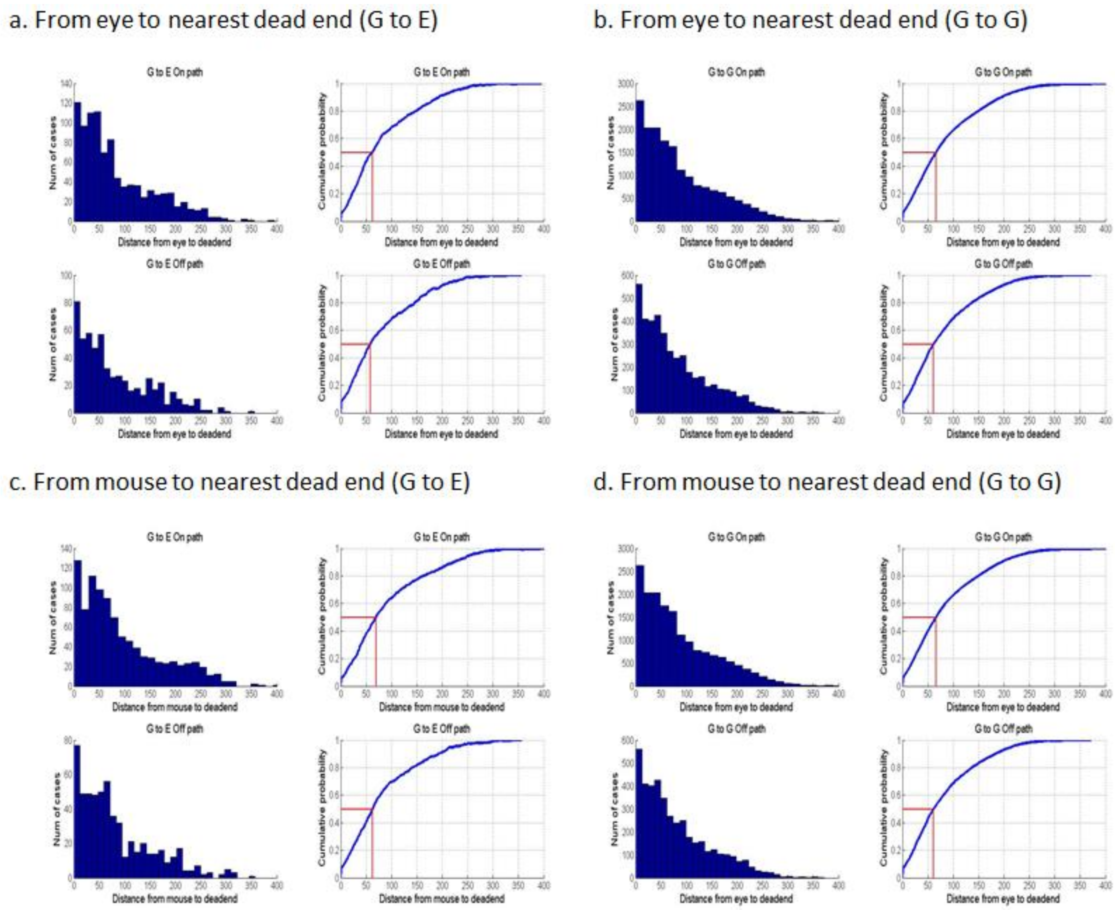


Figure 24. The histogram (columns 1 & 3) and cumulative probability plots (columns 2 & 4) of the distance from eye to the nearest dead end in Guidance to Exploration transitions (a), in Guidance to Guidance reference moments (b), from mouse to the nearest dead end in Guidance to Exploration transitions (c) and in Guidance to Guidance reference moments (d). All cases were separated into two groups: when the mouse cursor was off the correct path (rows 1 & 3) and when the mouse cursor was on the correct path (rows 2 & 4). The red lines in cumulative probability plots indicate the 50% threshold. The values of threshold were listed in Table 6.

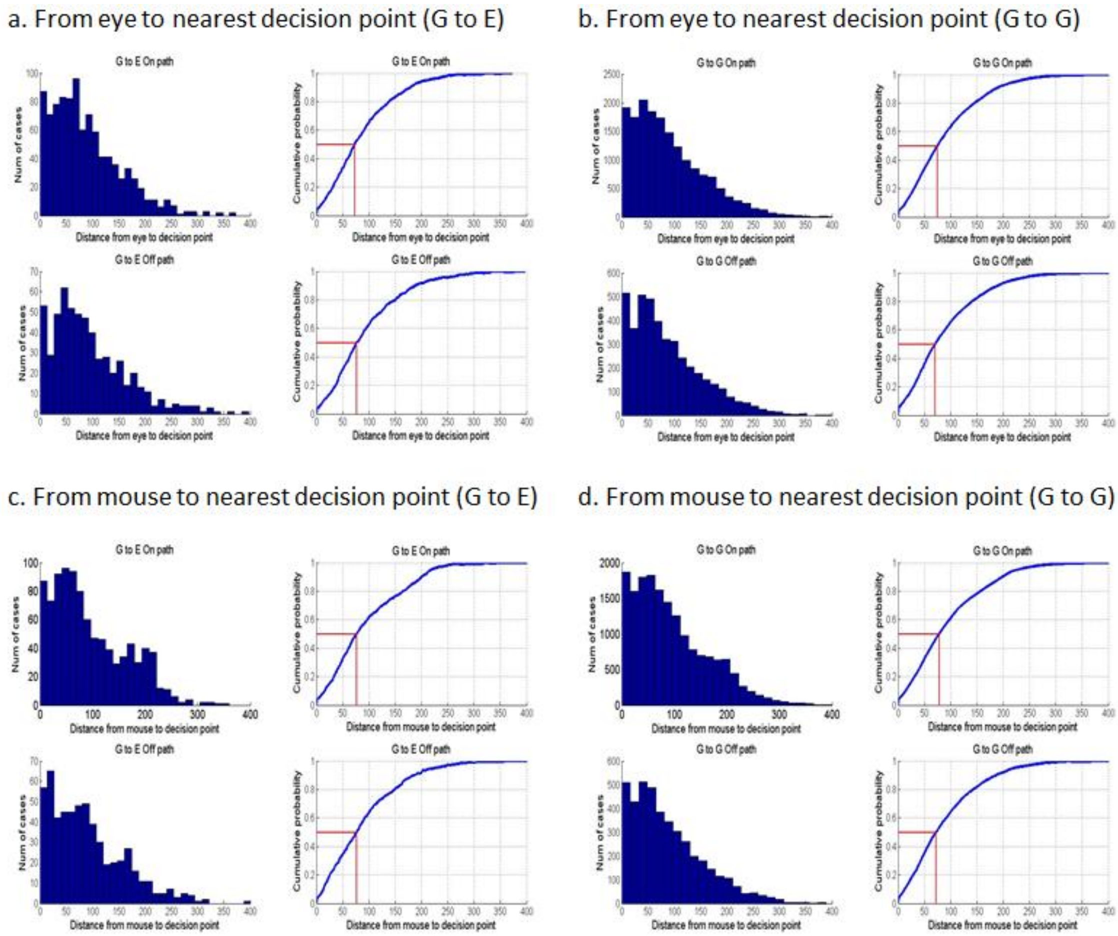


Figure 25. The histogram (columns 1 & 3) and cumulative probability plots (columns 2 & 4) of the distance from eye to the nearest decision point in Guidance to Exploration transitions (a), in Guidance to Guidance reference moments (b), from mouse to the nearest decision point in Guidance to Exploration transitions (c) and in Guidance to Guidance reference moments (d). All cases were separated into two groups: when the mouse cursor was off the correct path (rows 1 & 3) and when the mouse cursor was on the correct path (rows 2 & 4). The red lines in cumulative probability plots indicate the 50% threshold. The values of threshold were listed in Table 6.

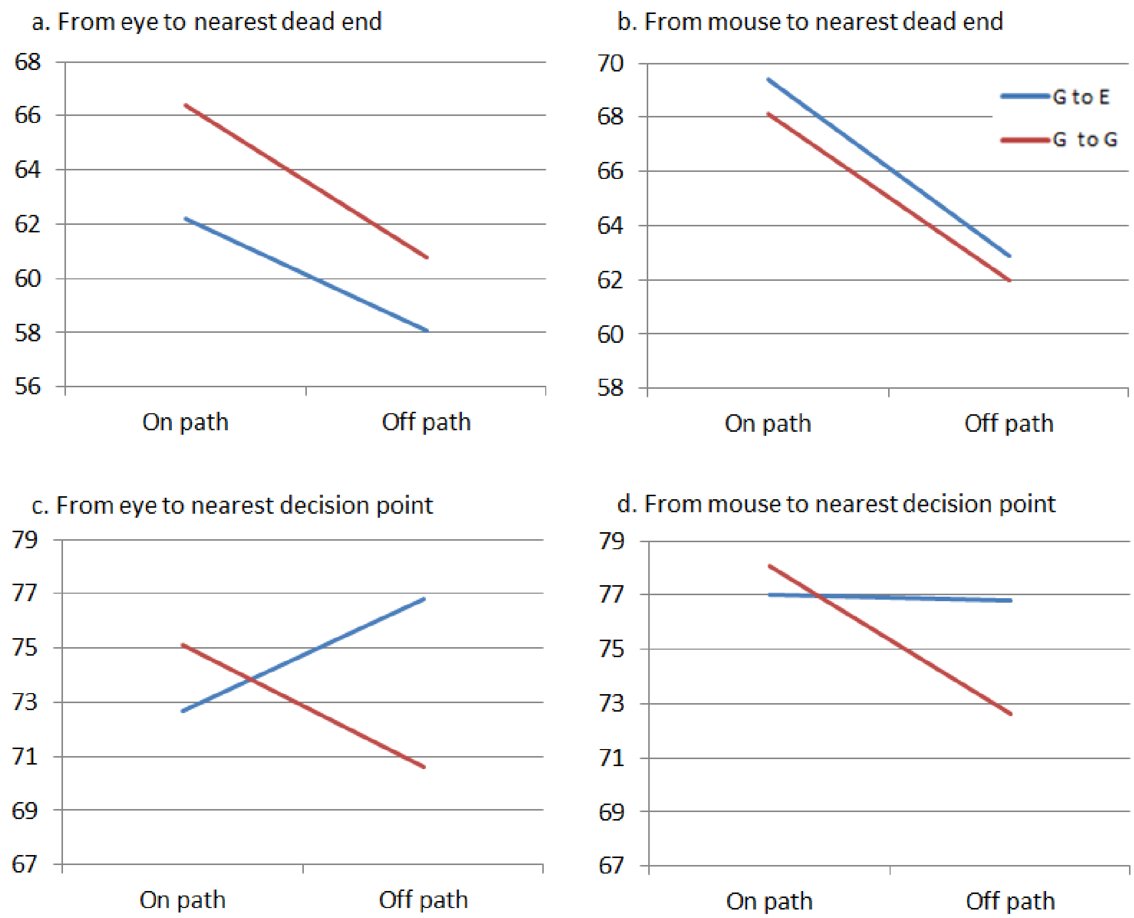
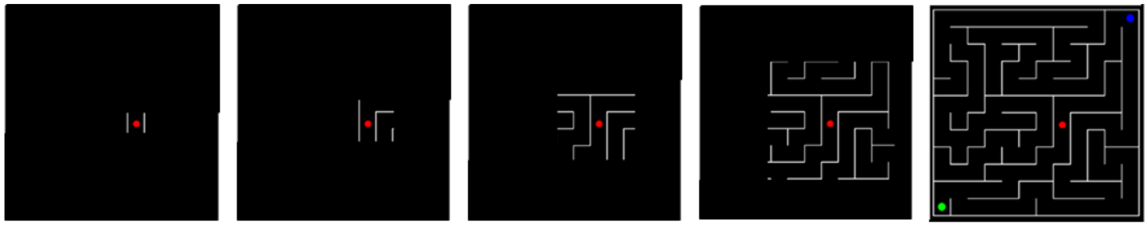


Figure 26. 50% thresholds, which were calculated from the cumulative probability plots for the distance from eye to the nearest dead end (a) and to the nearest decision point (c), and from mouse to the nearest dead end (b) and to the nearest decision point (d). There were two cases were plotted: transition moments (G to E, blue lines) and reference moments (G to G, red lines). All cases were separated into two groups: when the mouse cursor was off the correct path (Off path) and when the mouse cursor was on the correct path (On path). The values of these bars (50% threshold) could be found in Table 6.



a. 30 b. 60 c. 100 d. 200 e. 600

Figure 27. Five levels of view window size.

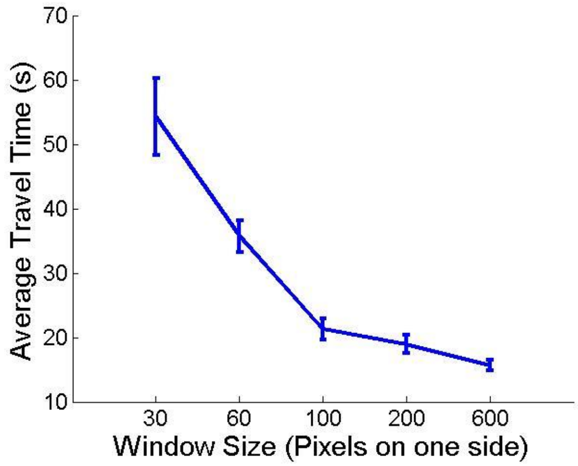


Figure 28. Mean travel time (s) as a function of visible window size. Error bars represent +/- 1 standard error.

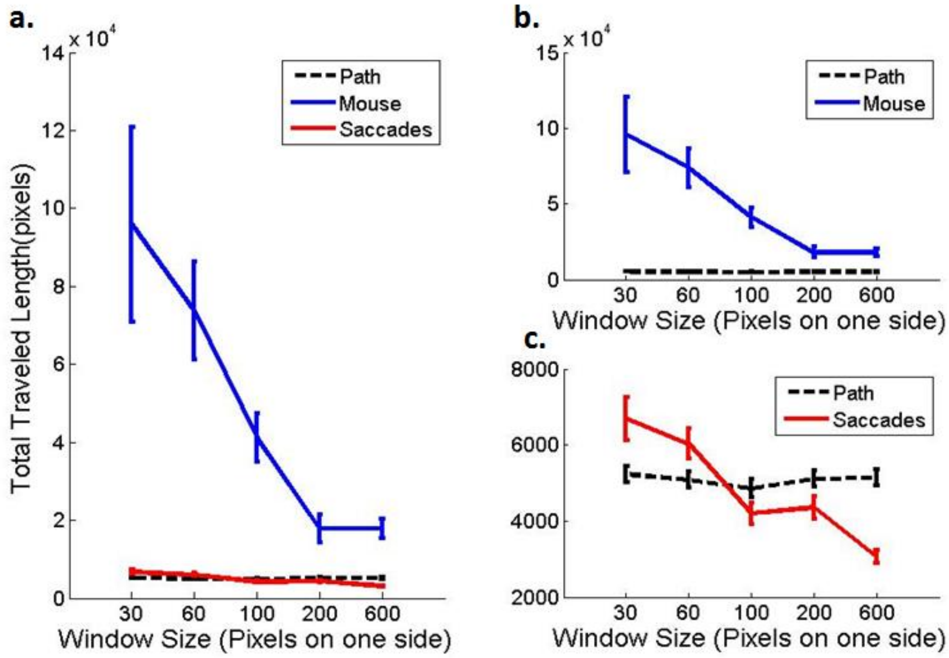


Figure 29. Mouse traveled length, total saccade length, and length of correct paths as a function of visible window size.

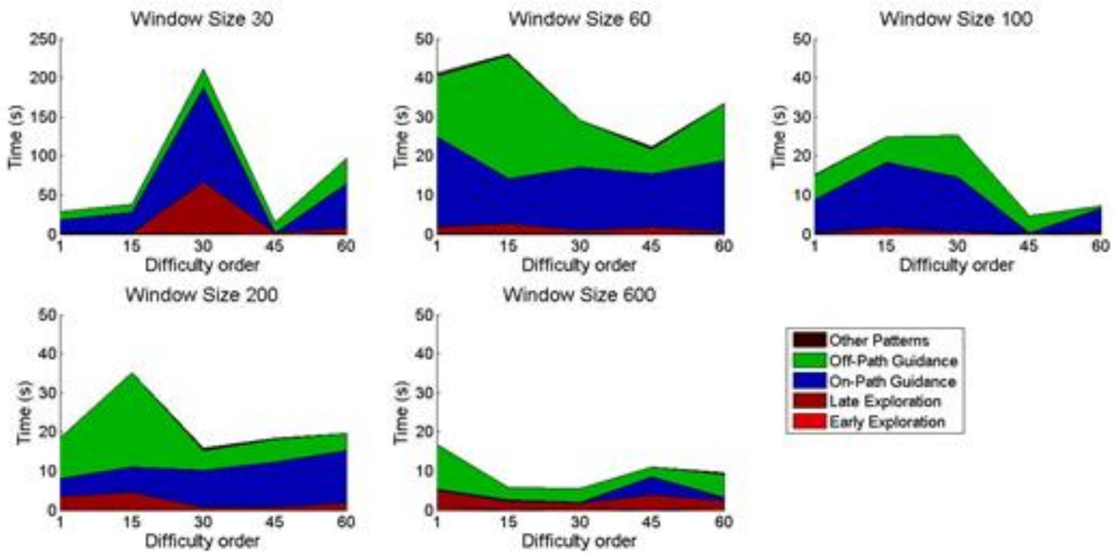


Figure 30 Times of different eye-hand coordination patterns in testing trials as a function of maze difficulty order, from Experiment 3 (Limited View). There were 5 levels of visible window size (30, 60, 100, 200 and 600 minarc^2). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

Appendices

Table A-1. Exploration vs. Guidance

		On-path Guidance	Off-path Guidance	Early Exploration	Late Exploration	Others
Mouse Speed		>= 70 pixels/s	>= 70 pixels/s	< 70 pixels/s	< 70 pixels/s	< 70 pixels/s
Mouse Position		On the correct path	Off the correct path			
Eye-mouse distance				> 50 pixels (Onset) and > 50 pixels (Offset)	> 50 pixels (Onset) and > 50 pixels (Offset)	< 50 pixels (Onset) or < 50 pixels (Offset)
When Occurred				Before the first mouse movements	After the first mouse movements	
Changes in eye-mouse distance from onset to offset	Previous Saccade	> 0	> 0	> 0 or < 0	> 0	
	Current Fixation	< 0	< 0	~= 0	~= 0	
	Following Saccade	> 0	> 0	> 0 or < 0	> 0 or < 0	

Table A-2. Two-way ANONVA for Training trials (Expected vs. Unexpected)

	Groups (MAZK vs. MAZU)	Spatial Conditions	Interaction
On_path_guidance	.41(.526)	2.23(.112)	.06(.945)
Off_path_guidance	.41(.523)	2.22(.114)	.01(.991)
Late_exploration	3.63(.059)	1.39(.253)	1.21(.303)
Early_exploration	24.68(.000)***	1.72(.186)	.6(.549)

Notes: Values are F-score (p-value). The significance were labeled as: * at .05 level; ** at .01 level; * at .001 level**

Table A-3. Two-way ANONVA for Training trials and Testing trials (Expected vs. Unexpected)

FORWARD	Groups (MAZK vs. MAZU)	Training vs. Testing	Interaction
On_path_guidance	.4(.532)	.04(.841)	.04(.844)
Off_path_guidance	.78(.381)	21.64(.000)***	.14(.713)
Late_exploration	1.71(.195)	9.58(.003)**	1.31(.256)
Early_exploration	9.03(.004)**	11.45(.001)***	4.8(.031)*

BACKWARD	Groups (MAZK vs. MAZU)	Training vs. Testing	Interaction
On_path_guidance	.21(.650)	.03(.862)	.02(.892)
Off_path_guidance	1.02(.316)	1.51(.223)	.12(.775)
Late_exploration	4.96(.029)*	1.74(.191)	1.29(.260)
Early_exploration	6.89(.011)*	5.87(.018)*	.56(.456)

ROTATED	Groups (MAZK vs. MAZU)	Training vs. Testing	Interaction
On_path_guidance	.04(.847)	.01(.926)	0(.995)
Off_path_guidance	0(.973)	.22(.637)	.23(.635)
Late_exploration	.8(.373)	.29(.594)	1.35(.250)
Early_exploration	5.3(.024)*	4.09(.047)*	4.45(.038)*

Notes: Values are F-score (p-value). The significance were labeled as: * at .05 level; ** at .01 level; * at .001 level**

Table A-4. Two-way ANONVA for testing trials (Expected vs. Unexpected)

	Groups (MAZK vs. MAZU)	Spatial Conditions	Interaction
On_path_guidance	.14 (.704)	2.96 (.056)	.01(.992)
Off_path_guidance	.5 (.480)	21.43 (0) ***	.52(.597)
Late_exploration	2.34 (.129)	23.32 (0) ***	.65(.523)
Early_exploration	1.3 (.256)	2.98 (.055)	.3(.739)

Notes: Values are F-score (p-value). The significance were labeled as: * at .05 level; ** at .01 level; * at .001 level**

Table A-5. Two-way ANONVA for testing trials (Expected vs. Preview)

	Groups (MAZK vs. MAZP)	Spatial Conditions	Interaction
On_path_guidance	.44 (.509)	3.23 (.043) *	.04(.962)
Off_path_guidance	1.32 (.253)	16.51 (0) ***	.37(.689)
Late_exploration	1.89 (.172)	23.34 (0) ***	1.26(.288)
Early_exploration	36.26 (0) ***	3.39 (.037) *	.49(.614)

Notes: Values are F-score (p-value). The significance were labeled as: * at .05 level; ** at .01 level; * at .001 level**

Table A-6. Two-way ANONVA (Training trials in Expected vs. Testing trials in Preview)

	Groups (MAZK training vs. MAZP testing)	Spatial Conditions	Interaction
On_path_guidance	.76(.386)	2.52(.085)	.13(.875)
Off_path_guidance	6.75(.011)*	5.69(.004)**	1.3(.276)
Late_exploration	7.48(.007)**	7.02(.001)***	6.56(.002)**
Early_exploration	101.34(.000)***	1.96(.146)	1.98(.142)

Notes: Values are F-score (p-value). The significance were labeled as: * at .05 level; ** at .01 level; * at .001 level**

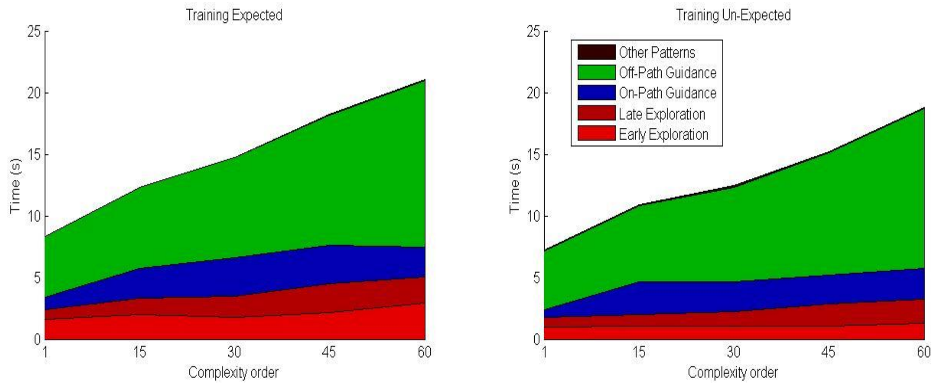


Figure A-1. Times of different eye-hand coordination patterns in training trials as a function of maze difficulty order, from "Expected" group (left plot) and "Un-Expected" group (right plot). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green). Only include lock lost free trials

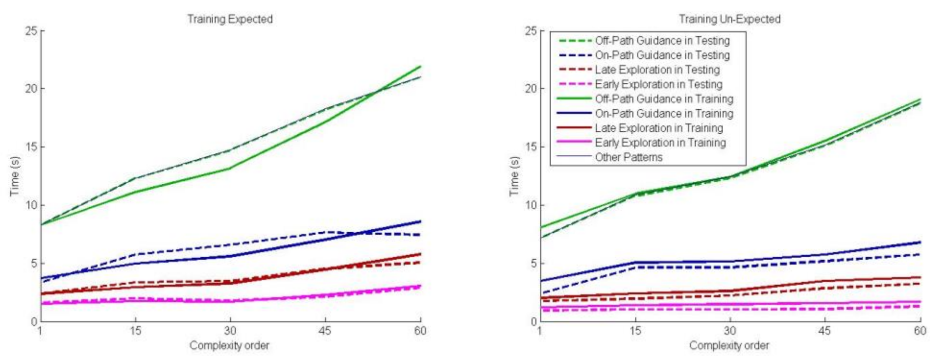


Figure A-2. Comparison between total trials and lock lost free trials

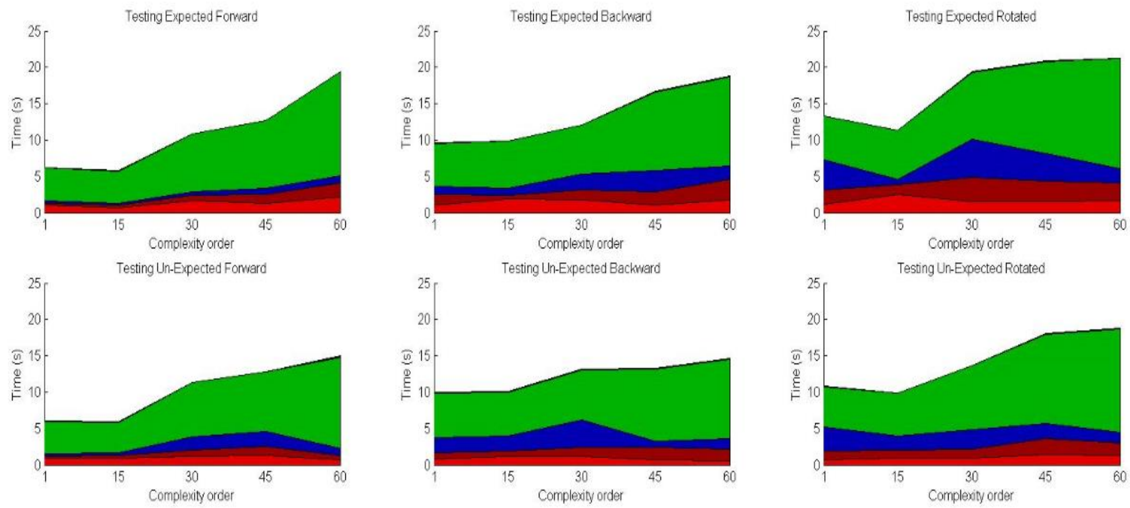


Figure A-3. Times of different eye-hand coordination patterns in testing trials as a function of maze difficulty order, from "Expected" group (upper plots), "Un-Expected" group (lower plots). 60 mazes were separated based on the spatial relationships (forward – left; backward – middle; rotated – right). There were four main patterns: early exploration (light red); late exploration (dark red); guidance when the mouse was off the correct path (blue); and guidance when the mouse was on the correct path (green).

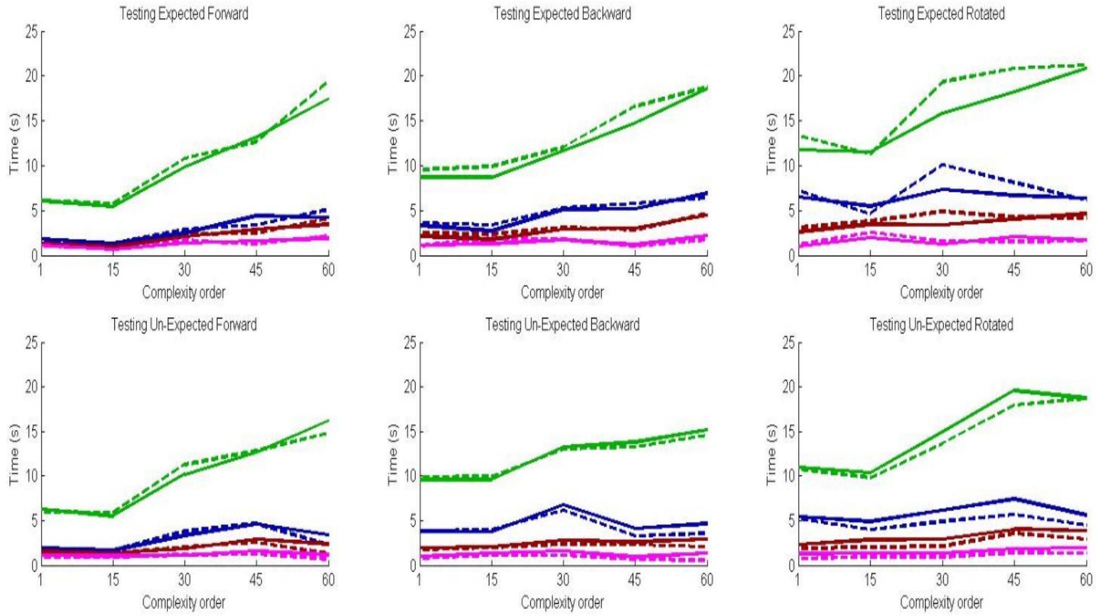


Figure A-4. Comparison between total trials and lock lost free trials

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