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# Spatial vision meets spatial cognition: Examining the effect of visual blur on human visually guided route learning

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**Abstract.** Visual navigation is a task that involves processing two-dimensional light patterns on the retinas to obtain knowledge of how to move through a three-dimensional environment. Therefore, modifying the basic characteristics of the two-dimensional information provided to navigators should have important and informative effects on how they navigate. Despite this, few basic research studies have examined the effects of systematically modifying the available levels of spatial visual detail on navigation performance. In this study, we tested the effects of a range of visual blur levels—approximately equivalent to various degrees of low-pass spatial frequency filtering—on participants' visually guided route-learning performance using desktop virtual renderings of the Hebb–Williams mazes. Our findings show that the function of blur and time to finish the mazes follows a sigmoidal pattern, with the inflection point around +2 D of experienced defocus. This suggests that visually guided route learning is fairly robust to blur, with the threshold level being just above the limit for legal blindness. These findings have implications for models of route learning, as well as for practical situations in which humans must navigate under conditions of blur.

## 1 Introduction

Visual navigation is a fundamental ability of animals that has been explored from a vast range of perspectives, so much so that the mouse in the maze has become an icon of psychology. Despite this wealth of research, there has been very little exploration of the basic spatial visual aspects of navigation. Although a great deal of applied and clinical work has been devoted to perceptual effects on this class of tasks, the effect of basic manipulations of spatial details as they apply specifically to route learning has not been parametrically examined. This is unfortunate, because route learning is an important aspect of navigation, and it is fundamentally a task that involves transforming two-dimensional spatial variations in luminance on the retinas into information about the observer's three-dimensional environment. Changes in the basic characteristics of the two-dimensional spatial inputs to the navigation system will no doubt have an impact on how one learns one's environment, and exploring such effects will almost certainly inform models of spatial cognition in important ways.

At the outset, we wish to define and constrain our use of the term 'navigation'. In its broadest sense, this term refers to an extensive array of tasks whose performance is affected by a wide range of variables. For example, navigation in real-world settings is affected by the nature and density of landmarks, as well as the availability of proprioceptive and vestibular cues. In the current work, we are interested in examining a narrow concept involving the use of visual information alone to learn a route from point A to point B in an environment, without the aid of explicit landmarks or proprioceptive cues. We therefore refer to our study as examining visually guided route-learning performance. This term is used to differentiate the construct we are examining from the larger concept of navigation in general.

In the present study, we provide an experimental examination of the effects of manipulating spatial frequency (SF) on visually guided route learning in humans.

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Specifically, we examine the effects of applying defocus, via spherical lenses of various strengths, on maze completion times on a desktop-style virtual environment. Our goal is to assess to what degree participants can tolerate spatial degradation of their view of an environment while completing a route-learning task. In doing so, we are motivated in part by findings regarding the effects of spatial filtering of stimuli on other visually guided tasks. We are also motivated by a number of practical issues, such as navigation by the visually impaired and by individuals experiencing artificially imposed blur, such as pilots wearing night-vision goggles. In the most general sense, we are interested in characterising the importance of fundamental features of visual information to spatial learning.

### 1.1 *Visual function and mobility*

While there has been little previous basic research on the effects of visual blur on mobility, there have been a few studies of similar issues. For instance, Vivekananda-Schmidt and colleagues (2004) examined the effects of diffusive blur on mobility performance in a real-world environment. They found that contrast sensitivity reductions caused by diffusive blur led to a significant impairment in performance. Participants were slower to walk through a room, and exhibited different visual examination strategies, when their contrast sensitivity was reduced by roughly a factor of two. This shows that reductions in available spatial visual information will have a significant effect on visually guided mobility. However, because Vivekananda-Schmidt et al described the route to their participants ahead of time, this study cannot tell us about the effects of blur on route learning. Another limitation of their study was their use of only two levels of contrast-sensitivity reduction, which is not enough to allow for information regarding the shape of the function linking spatial information and mobility.

One study that did vary visual function levels parametrically was that by Pelli (1986), who measured mobility performance of normally sighted participants after introducing varying levels of reduced visual acuity, contrast sensitivity, and visual field. Pelli found that it took a substantial reduction in each of these visual functions to produce an effect on performance. However, the routes used in this study were very basic, requiring participants to simply manoeuvre around a fairly open environment. Therefore, like the Vivekananda-Schmidt et al's study, Pelli's cannot inform us about the effect of blur on route learning.

Other relevant studies have dealt with more basic components of mobility and navigation than those examined in the present study. For instance, Heasley and colleagues (2004, 2005) examined the effect of wearing diffusion-causing lenses—designed to simulate cataracts—on the ability of visually normal older adults to take a step up to a higher level. They found that blur impaired task performance, and suggested that this was likely due, at least in part, to difficulty in seeing the step's edge. Vale et al (2008) examined a similar stepping task, but imposed blur using spherical lenses. They found that as little as +2 D of blur introduced to the dominant eye could significantly impair performance. These studies suggest that blur might impair edge detection in a navigation environment and that this might, in turn, be an important determinant of visually guided route-learning performance.

In addition to this basic research on the effect of blur on mobility, there has been a great deal of relevant work on clinical and applied aspects of navigation performance in the visually impaired (see eg Black et al 1997; Haymes et al 1994; Kuyk et al 1998a, 1998b; Marron and Bailey 1982; Patel et al 2006; Wood and Troutbeck 1994). Collectively, these studies have shown that a number of visual factors affect mobility performance in these populations, with the greatest effects coming from impairments of contrast sensitivity and visual-field deficits. In the present study, we were interested in measuring the effects of parametrically reduced visual acuity (spherical defocus) on

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route-learning performance. Although those studying visual impairment have generally found this factor to be less important for predicting mobility performance than other factors (see, eg, Marron and Bailey 1982; Owsley et al 2001; Patel et al 2006), others found it to have significant effects (see, eg, Brown et al 1986; Geruschat et al 1998; Haymes et al 1996). In the current study, we aimed to further examine the effect of visual acuity on visually guided route learning by parametrically altering visual acuity in isolation. This has not, to our knowledge, been done previously.

Those without visual impairment also sometimes face the necessity of navigating under conditions of visual blur. One example of such a situation concerns those using night-vision goggles (NVGs). Although these systems enhance luminance, they do not provide true daytime vision. The view through NVGs is impaired by visual field limitations, dynamic scintillating luminance noise, and—most germane to the current study—a significant degree of blur caused by quantisation (Gauthier et al 2008; Macuda et al 2005). The effect of this quantisation on navigation performance has been a concern, as NVG systems are routinely worn by soldiers and pilots who must navigate using them and there is evidence that their use is implicated in many accidents or near-accidents (Braithwaite et al 1998; Vyrnwy-Jones 1988). Although there have been a number of studies of the effects of NVGs on navigation and spatial awareness, none have dealt with the effects of the quantisation that they produce in isolation. Assessing the function of blur (similar to that caused by quantisation) and visually guided route-learning performance may therefore help guide the design of NVGs and similar systems in the future, possibly enhancing their safety.

### 1.2 *Spatial vision and visually guided cognitive tasks*

Whereas there has been relatively little basic research to date specifically devoted to the effects of blur manipulations on visually guided route learning, there has been a great deal of recent work examining the related concept of SF filtering that has made important inroads into understanding how certain other higher-order visually guided cognitive tasks are performed, particularly visual-recognition tasks. For instance, there is a large body of work on how SF manipulations affect face recognition (for a review, see Ruiz-Soler and Beltran 2006) and object identification (Biederman and Kalocsi 1997; Collin 2006; Collin et al 2004; Collin and McMullen 2005; Yue et al 2006). This has allowed the creation of powerful models of these processes that have a high degree of biological plausibility (Serre et al 2007; see also Yue et al 2006). The current study is motivated in part by the likelihood that similar sorts of explorations of the impact of spatial vision on spatial cognition will yield equally useful insights.

Two general findings have emerged from previous work on the interaction of spatial vision and higher-order cognitive tasks. One is that certain ranges of spatial information are most useful for a given specific task. For instance, in face recognition, a critical band of SFs has been established that seems to contain the information most useful for identification (Bachmann 1991; Costen et al 1994, 1996; Gold et al 1999; Nasanen 1999; Parker and Costen 1999). Object recognition, on the other hand, seems to be possible with a wide range of SFs (Biederman and Kalocsi 1997; Collin 2006; Collin et al 2004). The second general finding in this area is that there is a degree of cognitive penetrability into spatial vision, such that humans are able to attend particular frequency ranges when task demands make this beneficial (Ozgen et al 2006; Schyns 1998). This means that there is a degree of flexibility in the use of spatial visual information, and that human observers are able to extract the most useful available information in the stimulus presented to them.

While it may be that similar sorts of findings to the above will hold for visually guided route learning, there are obvious and important differences between this task and visual-recognition tasks that need to be considered. For instance, the stimuli in

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typical visual-recognition tasks are static relative to the observer. By comparison, in typical navigation tasks, the environment is in motion relative to the observer most of the time. This provides an important source of information that interacts in a vital way with spatial vision to provide the overall structure of the environment. A rich, moving, three-dimensional environment may provide sufficient higher-order visual cues that altering low-level information may have relatively little impact. This argues for a robustness of visually guided route-learning performance to visual blur, relative to performance with static images.

Another relevant difference between visual recognition—particularly face-recognition tasks—and route learning, is that the former often involves relatively homogeneous stimuli compared to way-finding tasks, which may take place in natural or artificial environments containing an almost infinite assortment of visual objects. Based on this, one might reason that a single critical band of SFs for visually guided route learning is unlikely. Nevertheless, there are some commonalities that can be relied upon in comparing visually guided route learning and visual-recognition tasks. For instance, although face recognition tasks typically involve homogeneous stimuli, object recognition tasks often use stimuli that range widely in their degree of heterogeneity, similar to mobility. Given that a wide range of SFs is useful for object recognition tasks even when discriminations are between exemplars within the same subordinate category (Biederman and Kalocsi 1997; Collin et al 2004), this again argues that a simple critical SF range for visually guided route learning is unlikely and that a wide range of frequencies may be useful for this task.

### 1.3 *Navigational paradigms*

A wide variety of experimental methodologies has been used to study navigation. Traditionally, navigation paradigms have generally fallen into two categories: in-lab tasks, such as studying routes on a map, and real-world navigation where participants actually navigate through the environment (for examples of both see, eg, Thorndyke and Hayes-Roth 1982). While each of these techniques has contributed useful insights into navigation, both have important limitations. It has been suggested that the use of maps or scale models in lab tests is not testing the construct of interest, spatial cognition, but may instead be a test of some altogether different construct, such as map reading ability. The use of real-world navigation environments solves this problem, since it clearly employs an ecologically valid task; however, it is limited by the difficulty in controlling many aspects of the environment through which the task is taking place, making it difficult to manipulate it satisfactorily (see Sandstrom et al 1998 for further discussion of these issues).

In more recent work, virtual environments are frequently used to explore navigation abilities, with the aim of combining the benefits of both in-lab and real-world navigation tasks. These virtual environments allow for greater generalisability to actual navigation, as spatial cognition can be examined in easily controlled environments through which the participants can navigate either physically or through simulation. The present study used a paradigm involving a desktop style of virtual environment. This consisted of a number of mazes through which participants navigated from a first-person perspective. Although the use of a desktop system has some limitations because it lacks the vestibular and proprioceptive information available in some immersive environments (Ruddle and Lessels 2006, 2009), it still allows for good control and precise measurement of navigation behaviour. Previous work has explored visual determinants of mobility in a virtual environment (Fortenbaugh et al 2007). In their study, Fortenbaugh et al specifically examined the effect of visual-field loss on mobility performance. However, owing to constraints in technology that included a limited rate at which the virtual environment image was updated, their virtual system involved a number of delays, leading to rough flow of movement through the environment

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(however, it should be noted that these delays did not significantly affect the results relative to a real-world navigation task—Fortenbaugh et al 2007, pages 559–560). For the current study we chose to use dioptric lenses to blur vision, rather than manipulate the computer-presented environment itself, in order to provide a real-time examination of this factor on visually guided route learning.

#### 1.4 *Outline and hypotheses*

In the present study, we examined the effect of visual blur, introduced by using spherical defocus, on visually guided route-learning performance in a desktop-style virtual environment. It is difficult to make precise quantitative predictions with respect to our findings owing to the limited previous research on this specific topic. As previously mentioned, those studies which have used a similar spherical defocus to ours have concentrated mainly on participants' movements while taking a step, and not on route learning as a whole (Vale et al 2008). While it is almost certain that performance will drop monotonically as visual blur increases, it is not clear a priori what the shape of the function will be. It is possible, for instance, that a gradual linear decline in performance will be observed as blur is increased. However, should we find a steep threshold-like function instead, it is likely that the position of this threshold on the SF spectrum will be quite low. We posit this for a number of reasons. First, if visually guided route learning is similar to object identification in its visual requirements, as we have argued above, then one would expect a broad range of SFs to be adequate for performance of the task. Also, visually guided route learning takes place in a relatively rich, three-dimensional environment with flow field information and other higher-order cues available, so degradation of low-level spatial information may have to be extreme before it affects performance. Finally, some studies have suggested that raw visual information is not of primary importance in mobility tasks (Ruddle and Lessels 2006, 2009), again suggesting that only a minimal degree of two-dimensional spatial information will be necessary. For all these reasons we predict that any detriment to visually guided route learning will occur at the low end of the SF spectrum.

## 2 **Experiment 1**

In experiment 1 we used spherical lenses of various positive dioptric strengths to alter the levels of visual detail available to participants as they navigated through a series of mazes presented from a first-person point of view. Each maze was navigated 5 times, allowing participants to progressively learn its layout. The lenses had effects roughly equivalent to applying low-pass spatial filters to the two-dimensional pictorial information available to the participants. The purpose of this experiment was to assess the function of SF cut-off on visually guided route learning. 'SF cut-off' here refers to the point on the SF spectrum beyond which an SF filter, such as a blurring lens, does not allow any information through. The more powerful the spherical defocus produced by the lens, the lower the SF cut-off point will be, and the blurrier the image will appear.

### 2.1 *Method*

2.1.1 *Participants*. Forty-eight undergraduate students from the University of Ottawa participated for either a small honorarium or course credit. Thirteen were unable to complete the experiment owing to experiencing dizziness or nausea. This low rate of completion is likely due to the visual blurring adding an additional challenge to the task for those prone to motion sickness. The mean age of the remaining thirty-five participants (seventeen females) was  $20.8 \pm 3.6$  years. All participants had normal or corrected-to-normal spatial vision as determined by contrast sensitivity testing with the Vision Contrast Test System (Vistech Consultants, Dayton, OH).

2.1.2 *Stimuli and materials.* Participants were asked to manoeuvre through a set of virtual mazes originally developed by MacInnes and colleagues (MacInnes 2004; MacInnes et al 2001; Shore et al 2001). These consist of three-dimensional renderings of the traditional Hebb–Williams mazes (Hebb and Williams 1946; Rabinovitch and Rosvold 1951) presented on a computer screen in a fashion similar to first-person-style video games. The mazes were generated with OpenGL graphics library routines in C++. In order to provide proper timing, the ‘Windows’ event handler was suspended while the program was running. Also, continuous keyboard monitoring was implemented to allow rapid response by the program to key presses by the participants.

An example view of one maze is shown in the top panel of figure 1. The walls, ceiling, and floor were rendered with fractal noise patterns. That is, the bitmaps applied to the three-dimensional structure of the maze consisted of an array of grey pixels selected at random from a Gaussian distribution of the 256 grey levels available in the 8-bit colour gamut. This bitmap was then put through an SF filter with a gain profile of  $1/f^{1.1}$  where  $f$  is the SF of the image components in a Fourier analysis. This filtering makes the amplitude spectrum of the bitmap equivalent to that of an average natural image (see, eg, Field and Brady 1997; Tolhurst et al 1992). In addition to providing a naturalistic amplitude spectrum to the participants’ views of mazes, using a fractal noise pattern also had the effect of making the maze walls have a similar level of structure at a wide range of virtual viewing distances. This pattern was repeated along all maze surfaces in order to provide an environment devoid of any landmarks.

The monitor’s luminance was calibrated for linearity. The average luminance of the maze images was determined to be  $66.6 \text{ cd m}^{-2}$ . Average luminance was determined by taking 30 arbitrary screen snapshots of the mazes, averaging the grey levels therein, and measuring the luminance of that average grey level on the same monitor with an LS-110 photometer.

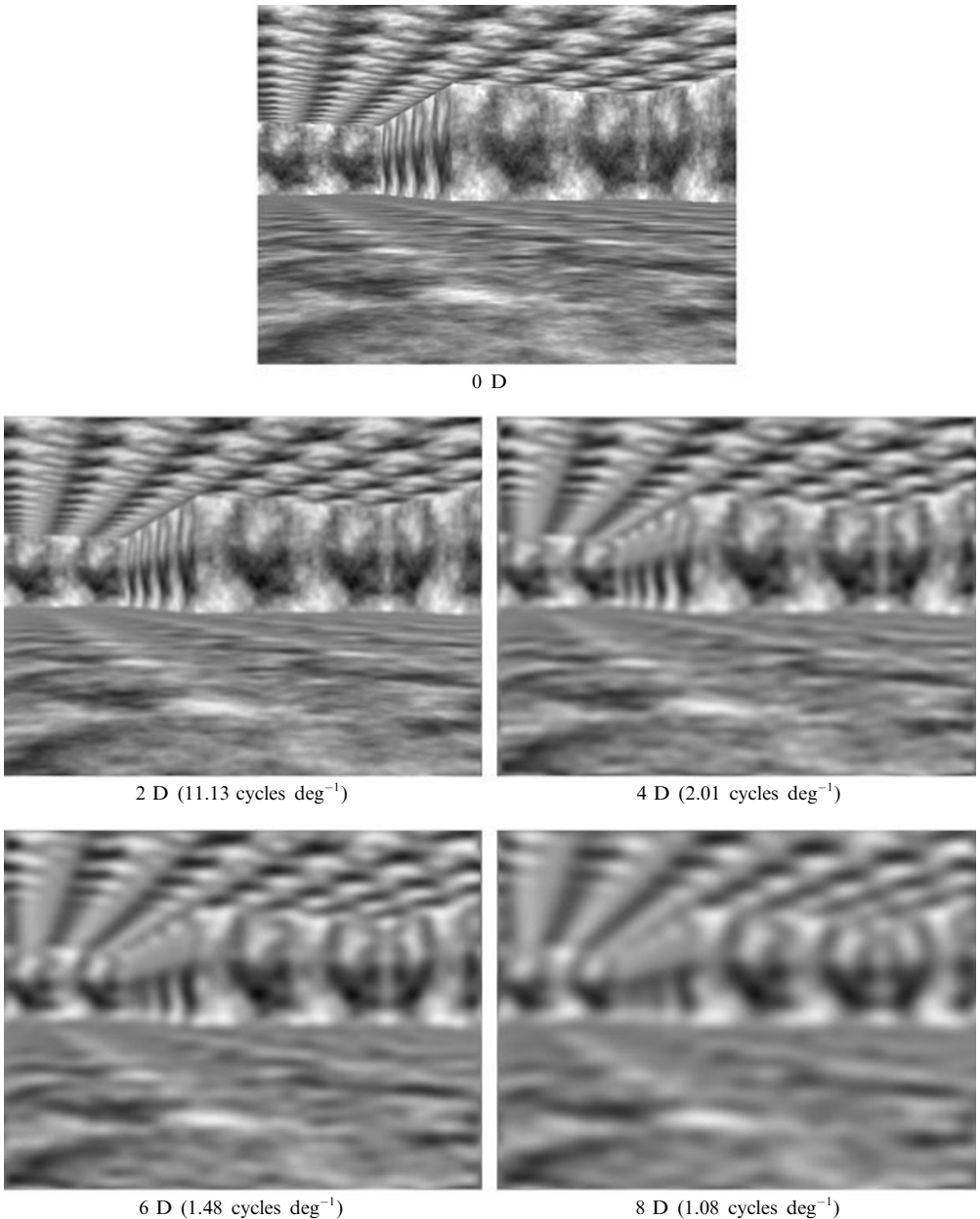
Participants moved through the maze by using the standard keyboard arrow keys. Assuming an average viewing height of 168 cm ( $\sim 5\frac{1}{2}$  feet) the rendering of the entire maze area was 20 metres on a side at scale. Movement speed was approximately  $12 \text{ km h}^{-1}$  at scale, with a turn rate of  $50^\circ \text{ s}^{-1}$  and a visual field of  $55^\circ$ .

As can be seen in figure 2, the structure of each maze was based on a  $6 \times 6$  grid with  $1 \times 1$  square alcoves at diagonally opposite corners. As with the original Hebb–Williams mazes, one of these alcoves always served as the start and the other as the goal. From the original set of 12 Hebb–Williams mazes, 10 were selected as the most difficult on the basis of the efficiency data of Shore et al (2001). From this subset of 10 mazes, 10 new ones were created by flipping the layout of the mazes right-to-left along a diagonal line extending from the start alcove to the goal alcove. This yielded a set of 20 mazes, as seen in figure 2.

From the 20 mazes, 5 groups of 4 mazes were created, such that each set had an equal overall mean of difficulty ranking based on Shore et al’s (2001) efficiency data. These groups of 4 mazes were presented in one of two fixed orders, with one order being the reverse of the other, for a total of 10 possible sets of 4 mazes. This had the effect of completely counterbalancing the order positions of the mazes across participants.

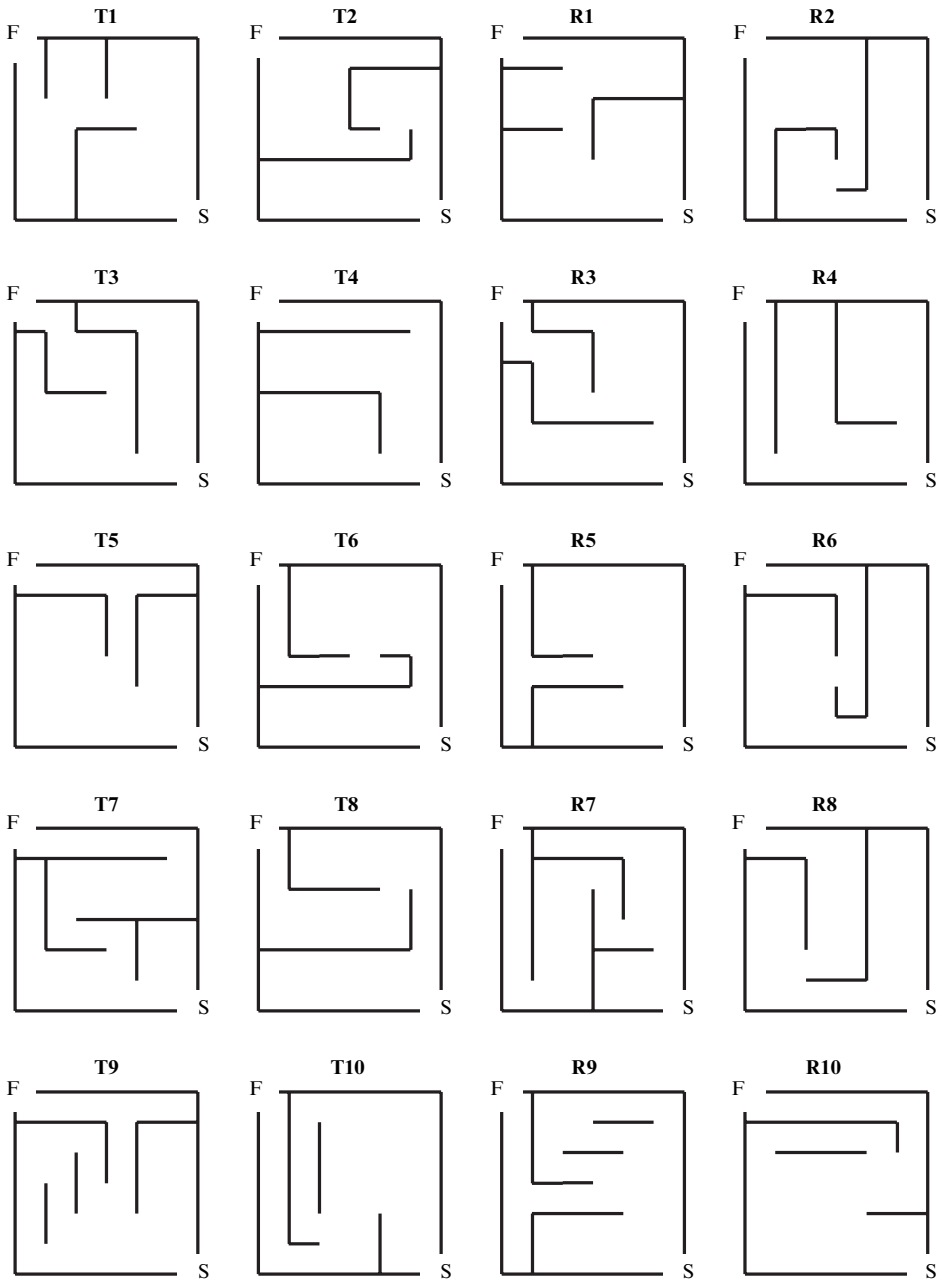
An ophthalmic trial frame and trial lenses were used to blur participants’ vision while navigating the mazes. The lens strengths used were: 0, +2, +4, +6, and +8 D. These were overlaid in the trial frame on top of lenses that matched each participant’s regular prescription, if any.

To better characterise the blur levels produced by these lenses, we calculated the modulation transfer function (MTF) of an average age-appropriate eye having +2, +4, +6, or +8D of defocus blur by using the formulas given in Appendix 1 of Akutsu et al (2000; see also Charman and Jennings 1976 and Smith 1982). To do this,



**Figure 1.** Examples of a scene from the virtual maze as presented to participants in experiment 1. The upper panel shows an unfiltered version of the scene. The lower four panels show filtered versions of the same scene, filtered to the levels experienced after accommodation, passed through a Butterworth low-pass filter (exponent 5) in order to provide an approximation of the view of the maze experienced by participants wearing lenses of +0.36, +2.01, +2.75, and +3.76 D of experienced blur. The 50% cut-offs applied are shown below each image.

we first tested the visual acuity of a group of seventeen age-matched participants ( $21.5 \pm 4.6$  years) when wearing the lenses at a distance of 85 cm (the same as the viewing distance in the experiments) with an ETDRS near acuity chart (Precision Vision, LaSalle, IL). Measured acuity levels were adjusted proportionally for the non-standard viewing distance. We then used these visual acuity levels to determine the actual mean defocus experienced by the participants, taking accommodation into account.



**Figure 2.** Overhead view of the 20 mazes used in experiments 1 and 2. S indicates the start of the maze and F indicates the finish. Mazes labeled T1–T10 are the original Hebb–Williams’s maze layouts, while the R1–R10 mazes are the mirror-reversed maze layouts.

This was done by linear interpolation between the values provided by Borish and Benjamin (1998) for equivalence between acuity and defocus. On the basis of these calculations, the mean experienced defocus for lenses of +2, +4, +6, and +8 D, was +0.36, +2.01, +2.75, and +3.76 D, respectively. We next calculated the SF at which the MTF of the experienced defocus level drops to 0.5 to get an approximation of the 50% cut-off value of a low-pass filter that would yield the same degree of blur.



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This yielded equivalent cut-offs of 11.13, 2.01, 1.48, and 1.08 cycles  $\text{deg}^{-1}$  for the experienced blur levels of +0.36, +2.01, +2.75, and +3.76 D, respectively.<sup>(1)</sup> Images filtered at these cut-off frequencies are shown in figure 1 to provide an approximation of what the participants saw during testing. These images were SF filtered with a Butterworth low-pass filter of order 5 in MATLAB at the cut-offs specified above. Note that for the rest of the methods, results, and discussion (including figures), the diopter strengths indicated will be the mean experienced defocus levels, as opposed to the strengths of the lenses.

The images in figure 1 subjectively match with participants' reports and our own informal observations of the degree of blur experienced when viewing the mazes through the various strengths of blurring lenses. However, the SF cut-offs given above can only be taken as approximations of the effects of the lenses for a number of reasons. For one, calculation of the MTF requires pupil size as a factor and this varies widely among individuals. The values given above are based on an average pupil diameter of 3.86 mm, calculated with Stanley and Davies's (1995) formula for pupil size as a function of luminance and stimulus size. This value was based on a stimulus diameter of 20.41 deg, derived from the fact that our screen area was  $15.77 \text{ deg} \times 20.75 \text{ deg} = 327.23 \text{ deg}^2$  (screen dimensions were 32.3 cm  $\times$  24.0 cm at a distance of 85 cm). This is equivalent in area to a circular stimulus of radius 10.21 deg (Stanley and Davies 1995). The other factor required for calculating average pupil size is the average luminance of the screen, which was  $66.6 \text{ cd m}^{-2}$ . This was measured as described above in the stimulus section. Although pupil size no doubt varied among participants, previous research indicates that this calculated average is very likely to be close to the group average in our sample (Stanley and Davies 1995), and therefore the SF cut-off estimates above should be reasonably accurate.

Maze stimuli were presented on an IBM ThinkCentre M50-COE with an AccuSync 900 monitor. A chin-rest was used to maintain a fixed viewing distance of 85 cm from the computer monitor.

A questionnaire was given to all participants prior to testing to gauge their previous relevant video-game experience (see Appendix). The questionnaire measures total lifetime hours spent playing computer and video games. It also asks specifically about hours spent playing first-person-style video games, of particular relevance here. Total lifetime hours spent playing video games and total lifetime hours spent playing first-person-style games were calculated for each participant from their answers to these questionnaires. The latter value was used as a covariate in the analyses.

**2.1.3 Procedure.** Participants were randomly assigned to two of four experienced defocus conditions—+0.36, +2.01, +2.75, or +3.76 D—and all participants underwent the 0 D baseline condition. Participants ran through these three blur conditions in random order. For each blur condition one of the 10 sets of 4 mazes (see description of maze stimuli, above) was chosen at random. Each of the 4 mazes was presented to the participant 5 times in succession.

<sup>(1)</sup>As Akutsu et al (2000) note, the optical MTF for dioptrically blurred targets has a series of negative and positive lobes above the first zero-crossing. That is, it does not simply drop smoothly from 1 to 0 as does a Butterworth or half-Gaussian filter, but instead has a series of rises and falls relative to 0 following the first zero-crossing. Here we simply ignored these additional lobes and calculated the frequency at which the function has a value of 0.5, which always occurs uniquely before the first zero crossing. If the information beyond the first zero crossing is useful, then SF filtering to the levels above will not yield the same performance as the associated level of dioptric blur (performance with the lobes included should be better). However, Akutsu et al (2000) note that applying spatial filters that mimic the effects of these lobes beyond the first zero-crossing yields no advantage in visual acuity testing when compared to leaving them off (what they call their 'truncated filter' condition).

Prior to doing the experiment, each participant was given the computer and video-game questionnaire. Participants were then fitted with the trial frame, and lenses were added to match their prescription glasses, if any. Those wearing prescription contact lenses were asked to leave them in.

To begin the experiment, a participant was first placed with his/her chin positioned in the chin-rest at a viewing distance of 85 cm. The participants were then shown a practice maze through which they navigated using keyboard keys until they felt comfortable with the arrow key controls. Next, the appropriate lens strength for the first blur condition was placed into the trial frame.

At this point, participants were given instructions. They were told that for each lens type they would be required to navigate through 4 mazes, each repeated 5 times in order for them to learn the routes in each maze and that they would participate in 3 lens conditions for a total of 60 maze runs. They were also told that their sole objective was to manoeuvre through the mazes as quickly as possible.

Participants were given a break between each new maze and encouraged to remove the trial frame while taking the break to give their eyes a rest. Once the first set of 4 mazes (5 runs each) had been completed, the lenses were exchanged with a new set by the experimenter and the participant navigated through a new set of 4 mazes. This occurred three times in total, so that each participant navigated through one set of mazes with the baseline 0 D lenses and two of the experienced blurring lens levels (+0.36, +2.01, +2.75, or +3.76 D) determined randomly for each participant such that every possible combination of two lens types was used multiple times. This resulted in total run numbers of 35 for the baseline 0 D conditions, 18 for the +0.36 and +2.01 D conditions and 17 for the +2.75 and +3.76 D conditions. For each run, the computer program automatically recorded the participant's path through the maze, number of errors—based on Hebb and Williams' (1946) error coding scheme—and time to completion.

After completing all 60 maze runs (3 sets of 4 mazes, run 5 times each), participants were debriefed as to the purpose of the experiment and given compensation.

## 2.2 Results and discussion

Completion time was recorded for all trials of all mazes. These data were subjected to a single-pass outlier-rejection procedure using a standard deviation cut-off based on the sample size in each lens condition (Van Selst and Jolicoeur 1994). Any lens condition for a participant that had 2 or more maze runs missing out of 5 (more than 40% missing data) due to the standard deviation cut-off, was eliminated. This eliminated one lens condition from each of five people, including one each of +2.01, +2.75, and +3.76 D and two of 0 D. All empty cells, including those generated by the outlier rejection and those caused by participants not completing all trials, were replaced with the mean for their particular lens type and maze run (Tabachnick and Fidell 2001). This replaced a total of 18 cells out of 525.

Results from our questionnaire regarding video-game experience showed that participants had a median of 624 h of lifetime experience playing first-person-style video games. The distribution was somewhat positively skewed, with an interquartile range of 0 to 1794 lifetime hours. Thus, there was a wide range of video-game experience levels.

Maze completion times were analysed with a  $5 \times 5$  mixed analysis of covariance (ANCOVA) with maze run (1st to 5th) as a within-subjects factor, experienced defocus (0, +0.36, +2.01, +2.75, and +3.76 D) as a between-subjects factor, and first-person-player video-game experience as a covariate. Despite the fact that our participants showed a wide range of experience levels with first-person-style video games, the covariate in the model did not substantively change the results and was therefore

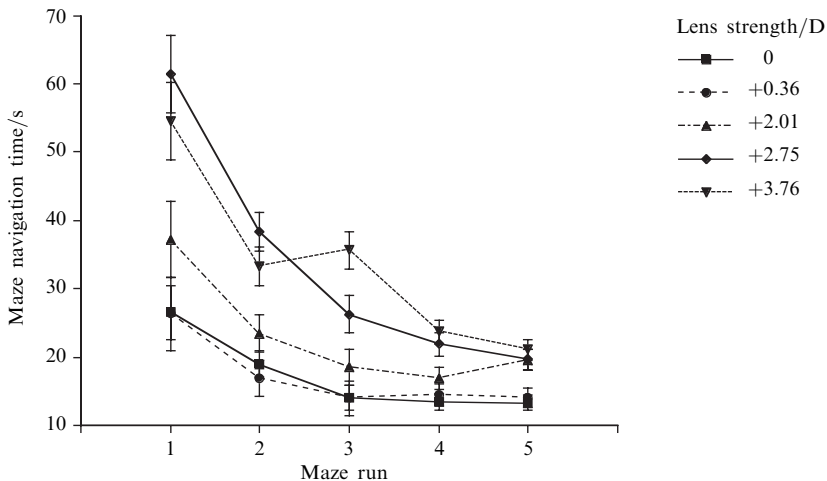
dropped from further analyses. Mean completion times and standard errors can be seen in figure 3. Participants show a fairly standard learning curve shape for all lens-strength levels.

The ANCOVA revealed a main effect of maze run ( $F_{1,944,182.702} = 60.086, p < 0.001$ ) with later runs being completed faster than earlier ones, as well as a main effect of lens type ( $F_{4,94} = 19.607, p < 0.001$ ) with stronger lenses resulting in slower maze completion times than weaker ones. Furthermore, a significant interaction between maze run and lens type was found ( $F_{7.775,182.702} = 4.386, p < 0.001$ ).

Simple main effects of lens type within each level of maze run revealed significant findings for all runs—run 1:  $F_{4,94} = 9.465, p < 0.001$ ; run 2:  $F_{4,94} = 12.717, p < 0.001$ ; run 3:  $F_{4,94} = 13.586, p < 0.001$ ; run 4:  $F_{4,94} = 8.732, p < 0.001$ ; and run 5:  $F_{4,94} = 7.399, p < 0.001$ . That is, lens strength continued to be a factor even after participants had thoroughly learned the maze.

To further analyse these simple main effects of lens strength, a posteriori one-way ANOVAs and *t*-tests were performed on all of the lens strengths for each level of maze run. Table 1 shows mean differences and significant levels for all a posteriori tests. This revealed that for run 1, the completion times under the 0, +0.36, and +2.01 D lenses were not significantly different from each other, nor were the completion times under the +2.75 and +3.76 D lenses from each other; however, these two groups of levels differed significantly from each other, with the latter group having slower completion times than the former. Generally, this same pattern of results occurred in the other runs, suggesting that a significant performance decrement occurs between the +2.01 and +2.75 D lenses, but that performance above and below this range is little affected by variations in visual blur.<sup>(2)</sup>

Figure 3 shows that, as expected, completion times generally get faster for each subsequent run for all of the lens conditions, following a standard learning-curve form.



**Figure 3.** Results from experiment 1. Mean maze completion times for each run under each lens condition. Error bars show  $\pm 1$  SEM.

<sup>(2)</sup>Minor exceptions to this overall pattern include the following: (1) In run 3 maze completion times under 0, +0.36, and +2.01 D lenses were not significantly different from each other and they all were significantly different from the completion times for +2.75 and +3.76 D lenses; however, the +2.75 and +3.76 D lenses were also found to be significantly different from each other, which was not the case for the other runs. (2) On run 5, the two groups of diopters shift somewhat, with completion times for the +2.01 D lens being equivalent to the +2.75 and +3.76 D lenses, making two new groups (0 and +0.36 D; +2.01, +2.75, and +3.76 D) which differ significantly from each other, with the latter having slower completion times than the previous.

**Table 1.** Mean differences (in seconds) between lens types (0, +0.36, +2.01, +2.75, and 3.76 D) under each level of maze run (run 1, run 2, run 3, run 4, and run 5).

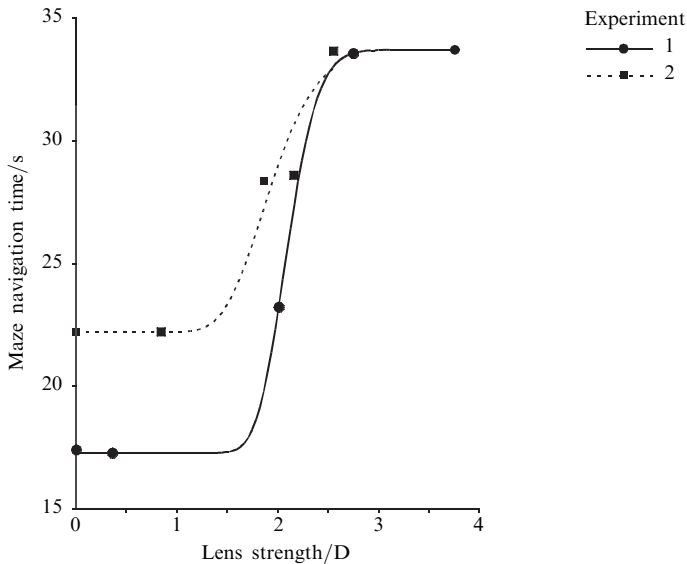
| Runs and lens type/D | Lens type/D        |                    |                    |                    |                    |
|----------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                      | 0 <sup>a</sup>     | +0.36 <sup>b</sup> | +2.01 <sup>b</sup> | +2.75 <sup>c</sup> | +3.76 <sup>c</sup> |
| <b>1</b>             |                    |                    |                    |                    |                    |
| 0                    | –                  | –                  | –                  | –                  | –                  |
| +0.36                | –0.24              | –                  | –                  | –                  | –                  |
| +2.01                | 10.59              | 10.83              | –                  | –                  | –                  |
| +2.75                | 34.81 <sup>t</sup> | 35.05 <sup>t</sup> | 24.22**            | –                  | –                  |
| +3.76                | 27.84 <sup>t</sup> | 28.08**            | 17.26*             | –6.96              | –                  |
| <b>2</b>             |                    |                    |                    |                    |                    |
| 0                    | –                  | –                  | –                  | –                  | –                  |
| +0.36                | –2.07              | –                  | –                  | –                  | –                  |
| +2.01                | 4.43               | 6.51               | –                  | –                  | –                  |
| +2.75                | 19.29 <sup>t</sup> | 21.37 <sup>t</sup> | 14.86 <sup>t</sup> | –                  | –                  |
| +3.76                | 14.28 <sup>t</sup> | 16.36 <sup>t</sup> | 9.85*              | –5.01              | –                  |
| <b>3</b>             |                    |                    |                    |                    |                    |
| 0                    | –                  | –                  | –                  | –                  | –                  |
| +0.36                | –0.017             | –                  | –                  | –                  | –                  |
| +2.01                | 4.55               | 4.53               | –                  | –                  | –                  |
| +2.75                | 12.22 <sup>t</sup> | 12.20**            | 7.67*              | –                  | –                  |
| +3.76                | 21.61 <sup>t</sup> | 21.60 <sup>t</sup> | 17.06 <sup>t</sup> | 9.39*              | –                  |
| <b>4</b>             |                    |                    |                    |                    |                    |
| 0                    | –                  | –                  | –                  | –                  | –                  |
| +0.36                | 1.01               | –                  | –                  | –                  | –                  |
| +2.01                | 3.38               | 2.38               | –                  | –                  | –                  |
| +2.75                | 8.45 <sup>t</sup>  | 7.24**             | 5.06*              | –                  | –                  |
| +3.76                | 10.27 <sup>t</sup> | 9.26 <sup>t</sup>  | 6.89**             | 1.83               | –                  |
| <b>5</b>             |                    |                    |                    |                    |                    |
| 0                    | –                  | –                  | –                  | –                  | –                  |
| +0.36                | 0.63               | –                  | –                  | –                  | –                  |
| +2.01                | 6.23**             | 5.60**             | –                  | –                  | –                  |
| +2.75                | 6.29**             | 5.66**             | 0.06               | –                  | –                  |
| +3.76                | 7.74 <sup>t</sup>  | 7.11**             | 1.51               | 1.45               | –                  |

Note: <sup>a</sup> $n = 35$ ; <sup>b</sup> $n = 18$ ; <sup>c</sup> $n = 17$ . \* $p < 0.05$ ; \*\* $p < 0.01$ ; <sup>t</sup> $p < 0.001$ .

ANCOVA and a posteriori analyses also showed that completion times tend to get faster with each run.<sup>(3)</sup>

The data analyses discussed above suggest a performance decrement between +2.01 and +2.75 D of blur. To further examine this issue, completion-time data were collapsed across maze run in order to visualise the effect of lens strength overall. As can be seen with the solid in figure 4, this results in sigmoidal functions for all lens strengths, a typical difficulty-by-performance relationship. In an attempt to characterise the inflection point of these functions, we fitted them with a cumulative normal distribution and calculated the point at which they reached the 50% point between run 1 and run 5 completion times. This showed a mean inflection point of around +2.09 D. This is compatible with the ANCOVA analyses discussed above, suggesting a performance decrement somewhere between +2.01 and +2.75 D.

<sup>(3)</sup>There are two exceptions to this pattern of completion times getting faster with each run. One occurs in the +3.76 D lens condition, where completion time is longer, though not significantly so, in run 3 than run 2. This is likely a product of the extreme variability found in this task due to the difficulty associated with it. The other exception is for the +2.01 D lens where completion times are longer for run 5 than run 4. This difference is small in magnitude, at 2.756 s, but is nonetheless statistically significant ( $p = 0.029$ ).



**Figure 4.** Mean maze completion times (collapsed across runs) for each lens type for experiment 1 and experiment 2.

### 3 Experiment 2

In order to better understand the function of maze completion times and lens strength around the +2.09 D level we extended experiment 1 by examining finer gradations of lens strength—and therefore finer gradations of low-pass SF filtering—around that point. Several methodological improvements were also implemented. First, each participant received all five lens conditions so that experiment 2 was a completely within-subjects experiment. In addition to this, the maze pairings that were created were better equated for difficulty, as will be discussed in section 3.1.2.

#### 3.1 Method

**3.1.1 Participants.** Forty-eight participants from the University of Ottawa volunteered for this experiment. Of these, seven were unable to complete it because they experienced headaches and/or nausea during the study. One additional participant was eliminated owing to his misunderstanding of the instructions and subsequent removal of the trial frame during test trials. The remaining forty participants (twenty-one female) had a mean age of  $22.7 \pm 5.0$  years. None of the participants had taken part in experiment 1 and all were naive as to the purpose of the study. All participants had normal or corrected-to-normal vision and received either a small honorarium or course credit for a psychology course as compensation for their participation.

**3.1.2 Stimuli and materials.** The stimuli and materials were the same as for experiment 1 except that the four lens strengths used were +3.0, +3.75, +4.5, and +5.25 D. In order to take accommodation into account, we tested the same age-matched control group as in experiment 1 on their relative acuities while wearing each of the lenses at a distance of 85 cm using an ETDRS near-acuity chart (Precision Vision Inc., LaSalle, IL). This yielded actual experienced blur levels of +0.84, +1.86, +2.15, and +2.55 D for the +3.0, +3.75, +4.5, and +5.25 D lenses, respectively. We then characterised the effects of these lenses in terms of an approximate low-pass SF cut-off for the actual dioptric blur experienced, resulting in equivalent cut-offs of 4.82, 2.17, 1.88, and 1.59 cycles  $\text{deg}^{-1}$  for the experienced blur levels of +0.84, +1.86, +2.15, and +2.55 D, respectively. As with experiment 1, for the remainder of the methods, results,

and discussion (including figures), we will discuss diopter strengths in terms of the levels experienced after taking accommodation into account. Once again a 0 D baseline condition was included.

An additional difference from experiment 1 was that maze sets in experiment 2 were created by a slightly different procedure. First, maze difficulty was determined by taking the average efficiency score across all 5 trials of each maze, rather than just the slowest and fastest runs, as was done for experiment 1.<sup>(4)</sup> Mazes were then paired with equivalent overall efficiency ratings for each pair. This created a total of 5 pairs for the 10 mazes and another 5 pairs were created which were simply the reverse order of the original 5. Each pair contained 1 original maze and 1 reversal maze so that all mazes were presented an equal number of times.

**3.1.3 Procedure.** The procedure for experiment 2 was the same as for experiment 1 except that each participant received all five lens conditions and only navigated through 2 mazes per lens (repeated 5 times each). Thus the design was completely within-subjects.

### 3.2 Results and discussion

As in experiment 1, completion times for each maze under each run and lens condition were recorded. Data were subjected to a single-pass outlier rejection procedure with a cut-off based on the sample size (Van Selst and Jolicoeur 1994). Next, each participant's data were examined to determine if any had greater than 40% missing data (6 or more cells missing out of 25). One such participant was found and that individual's data were removed from the analysis, leaving 39 participants (20 female). Finally, all remaining empty cells were replaced with the mean of their lens type and maze run (Tabachnick and Fidell 2001). In all, these procedures replaced a total of 32 cells out of 975.

Results from our questionnaire regarding video-game experience showed that participants had a median of 312 hours of lifetime experience playing first-person style video games. Again, the distribution was somewhat positively skewed and quite broad, with an interquartile range of 0 to 1560 lifetime hours.

A  $5 \times 5$  repeated ANCOVA was used to analyse these data with maze run (1st to 5th) and lens strength (0, +0.84, +1.86, +2.16, and +2.55 D) as within-subjects factors, and first-person player video-game experience as a covariate. As with experiment 1, inclusion of the covariate had no effect on the results and was therefore dropped from subsequent analyses. As can be seen in figure 5, the results from experiment 2 follow the same pattern as those from experiment 1.

The ANCOVA revealed a main effect of maze run ( $F_{2,525,294,184} = 48.008, p < 0.001$ ), with later runs being navigated faster than earlier runs, as well as a main effect of lens type ( $F_{2,914,294,184} = 11.513, p < 0.001$ ), with weaker lenses resulting in faster maze completion times than stronger lenses. More importantly, a significant interaction was found between maze run and lens type ( $F_{7,951,294,184} = 2.938, p = 0.004$ ).

In order to examine the effect of lens strength within each level of maze run, simple main effects analyses were performed. These revealed significant effects of lens for all runs—run 1:  $F_{4,34} = 7.150, p < 0.001$ ; run 2:  $F_{4,34} = 6.055, p = 0.001$ ; run 3:  $F_{4,34} = 6.993, p < 0.001$ ; run 4:  $F_{4,34} = 5.816, p = 0.001$ ; and run 5:  $F_{4,34} = 5.385, p = 0.002$ . A posteriori analyses showed an overall pattern of results that replicates

<sup>(4)</sup>Owing to an error in the efficiency calculation, the two most difficult mazes were switched such that the second most difficult maze was paired with the easiest maze and the most difficult maze was paired with the second easiest maze. However, this should not have caused any difference to the results for two reasons. First, it was two mazes adjacent to each other in the difficulty rankings that were switched so the difficulty rating between them was fairly small. Second, since all maze pairs were randomly assigned to lens conditions, the mistaken pairs were found equally in all five lens conditions, so that no lens condition would receive them any more than any other lens condition.

experiment 1. That is, completion times get faster across maze runs and slower across lens strengths in almost all cases. See table 2 for the mean difference and significance levels of all a posteriori tests.

Generally, performance levels with the +1.86, +2.16, and +2.55 D lenses were statistically indistinguishable from each other throughout the runs, while the completion times for the 0 D lens were significantly faster than for this group of lenses. The +0.84 D lens fluctuated between having completion times statistically the same as the 0 D lens, the stronger set of lenses, or both.

**Table 2.** Mean differences (in seconds) between lens types (0, +0.84, +1.86, +2.16, and +2.55 diopters) under each level of maze run (run 1, run 2, run 3, run 4, and run 5).

| Runs and lens type/D | Lens type/D        |         |        |        |       |
|----------------------|--------------------|---------|--------|--------|-------|
|                      | 0                  | +0.84   | +1.86  | +2.16  | +2.55 |
| <b>1</b>             |                    |         |        |        |       |
| 0                    | —                  | —       | —      | —      | —     |
| +0.84                | 7.36               | —       | —      | —      | —     |
| +1.86                | 18.32**            | 10.96   | —      | —      | —     |
| +2.16                | 19.80**            | 12.44   | 1.48   | —      | —     |
| +2.55                | 24.61 <sup>t</sup> | 17.25*  | 6.29   | 4.81   | —     |
| <b>2</b>             |                    |         |        |        |       |
| 0                    | —                  | —       | —      | —      | —     |
| +0.84                | 3.54*              | —       | —      | —      | —     |
| +1.86                | 16.24**            | 12.70*  | —      | —      | —     |
| +2.16                | 10.79**            | 7.25*   | -5.45  | —      | —     |
| +2.55                | 17.32*             | 13.78*  | 1.07   | 6.53   | —     |
| <b>3</b>             |                    |         |        |        |       |
| 0                    | —                  | —       | —      | —      | —     |
| +0.84                | 3.88*              | —       | —      | —      | —     |
| +1.86                | 8.29**             | 4.40    | —      | —      | —     |
| +2.16                | 10.37**            | 6.49    | 2.09   | —      | —     |
| +2.55                | 23.85 <sup>t</sup> | 19.97** | 15.57* | 13.48* | —     |
| <b>4</b>             |                    |         |        |        |       |
| 0                    | —                  | —       | —      | —      | —     |
| +0.84                | 2.99*              | —       | —      | —      | —     |
| +1.86                | 4.81**             | 1.83    | —      | —      | —     |
| +2.16                | 5.15**             | 2.17    | 0.34   | —      | —     |
| +2.55                | 5.62*              | 2.64    | 0.81   | 0.47   | —     |
| <b>5</b>             |                    |         |        |        |       |
| 0                    | —                  | —       | —      | —      | —     |
| +0.84                | 2.08               | —       | —      | —      | —     |
| +1.86                | 2.82*              | 0.75    | —      | —      | —     |
| +2.16                | 5.48**             | 3.40    | 2.66   | —      | —     |
| +2.55                | 5.59*              | 3.52    | 2.77   | 0.11   | —     |

Note:  $n = 39$ . \* $p < 0.05$ ; \*\* $p < 0.01$ ; <sup>t</sup> $p < 0.001$ .

The data analyses discussed above suggest a performance decrement between +0.84 and +1.86 D, in roughly the same range as in experiment 1 (+2.09 D). As with experiment 1, we collapsed the completion time data across maze runs in order to quantitatively examine the effect of lens strength overall. As expected, this results in sigmoidal functions for all lens strengths (see the dotted line of figure 4). We fit these data with a cumulative log  $x$ -normal distribution and calculated the inflection point at which completion times reached the 50% level between run 1 and run 5 completion times. This showed a mean inflection point of around +1.91 D.

In sum, the results of experiment 2 match those of experiment 1 quite well, although there seems to be a slight improvement in performance in the second experiment. Taken together, the two experiments suggest that the effect of blur on visually guided route learning is nonlinear, with a significant decrement occurring at around +2 D of optical blur.

#### 4 General discussion

In order to understand any visually guided task, it is important to understand the visual inputs the task requires. Relatively few basic studies have examined the effect of optical blur on visually guided mobility performance and no study that we are aware of has examined the effects of parametrically modifying spherical defocus on route learning. The purpose of the current study was to provide an examination of the effect of spatial degradation of the visual environment on spatial learning. Spatial degradation was achieved by systematically varying the levels of SFs available to participants via spherical defocus. Of particular importance was exploring the shape of the function produced by these manipulations. As indicated previously, we expected the function to drop monotonically, and to exhibit a rapid drop-off at a threshold point located in the low end of the SF spectrum.

Both experiments reported in the present study agree with our expectations, pointing towards a low SF threshold below which visually guided route-learning performance drops off rapidly. This pattern is similar to what has been found with other higher-order cognitive tasks with regard to the effects of SF filtering (eg Collin 2006; Ruiz-Soler and Beltran 2006). Both of our experiments suggest that under the conditions tested here, an inflection point around 2 cycles  $\text{deg}^{-1}$  exists in the function of maze completion time and low-pass SF cut-off. In experiment 1, a threshold of +2.09 D (approximately equivalent to a 1.94 cycles  $\text{deg}^{-1}$  low-pass SF filter cut-off) was found, while a threshold of +1.91 D (approximately equivalent to a 2.12 cycles  $\text{deg}^{-1}$  low-pass SF filter cut-off) was found for experiment 2.

Interestingly, the threshold of 2 D found in the present studies is just above the 2.5 D limit that typically produces a visual acuity of 20/200 (or legal blindness—Bailey 1998). It must be noted, however, that the relationship between dioptric strength and experienced visual acuity is complicated by things like ocular aberrations (Atchison et al 1998), such that 2.5 D may not cause 20/200 acuity for all subjects. However, our results still show that visually guided route learning in an environment devoid of explicit landmarks and distractors can be accomplished with fairly impoverished spatial information. This is in line with our prediction that any detriments to visually guided route learning would occur at a fairly low SF cut-off. As previously outlined, there are a number of reasons to expect robustness to spatial filtering in the visually guided route-learning task we have examined. First, route learning involves movement through an environment filled with objects. Even in the simple environments we have used in the current experiments, walls, corridors, and openings act like sharp-edged objects that mark locations where decisions must take place. Given that object recognition has been shown to be fairly resistant to SF changes (Biederman and Kalocsai 1997; Collin 2006; Collin et al 2004), it is unsurprising that visually guided route learning would show similar performance levels under a broad range of SFs above the threshold. This is not to say that visual discrimination of objects in the environment is entirely unaffected by spatial visual manipulations. For instance, a number of studies examining step climbing in older populations found that participants increased the amount of toe clearance from the step under impaired vision, indicating potential difficulties in detecting the edge of the step (Heasley et al 2004, 2005; Vale et al 2008). However, given our results, there is still clearly a robustness associated with spatial filtering to sharp-edged objects, such as the openings found in our environments.



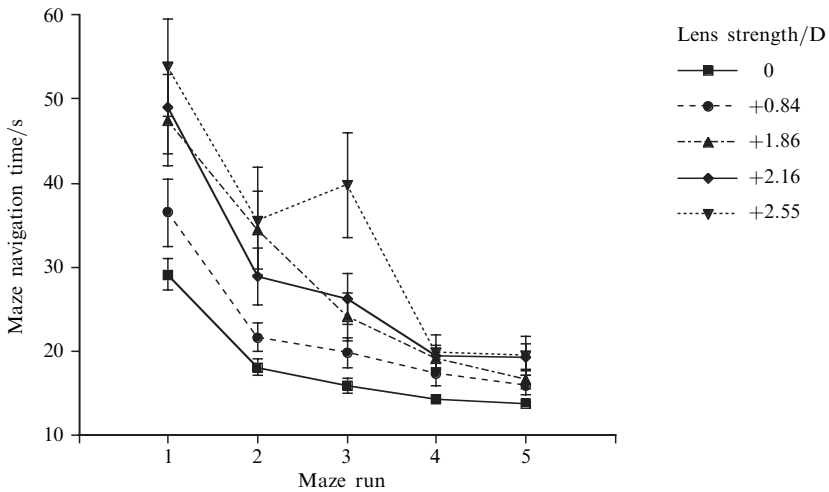
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A second reason why route-learning performance might be resistant to SF filtering is the richness of the environment. In contrast to stimuli typically used in experiments on the effects of spatial information manipulations on recognition tasks, typical mobility tasks occur in an environment involving higher-order motion cues. It therefore follows that changes to low-level visual processes, such as spatial vision, might not have as much influence as the higher-order information and would need to be quite extreme to cause an effect.

In terms of models of route learning, our results suggest that, under the parameters that we have examined here, there is a lower limit to the range of basic spatial information that is useful for this task, although it is low on the spectrum compared with that for recognition tasks. This suggests that early inputs from areas like V1 may be effectively filtered prior to being processed by later modules responsible for dealing with representations of environments. It has been suggested that this is the case with other processes, such as face recognition (Nasanen 1999) and that such filtering may reflect a divide-and-conquer strategy in the brain that serves to reduce the processing burden inherent in higher-order tasks. However, as Schyns and colleagues have pointed out (Ozgen et al 2006; Schyns 1998), there is a high degree of cognitive penetrability to SFs, in the sense that attention can be directed to different levels of spatial scale. Because of this, we cannot conclude that the limit we have found here represents the edge of a preferred or 'optimal' range for visually guided route learning; rather, this represents a potential absolute lower limit for useful information for the task. It may be that the optimal band for visually guided route learning (if any) has a lower cut-off higher in the spectrum, and that the  $\sim 2$  cycles  $\text{deg}^{-1}$  limit found here applies only to cases where a broader spectrum of information is unavailable. Further research will be needed to determine if this is the case.

One of the novel contributions our study makes to the literature investigating the effect of visual blur on mobility is in our ability to measure learning effects. By requiring our participants to navigate through each maze five times sequentially, we were able to measure how performance improved under the various blur conditions. In both experiments, performance showed significant improvement from one run to the next in almost all cases. This was true under all lens by run conditions, with only minor exceptions (see footnotes 3 and 4). Interestingly, by run 4, participants in all lens conditions appear to have reached a plateau in their time to complete the mazes. However, the level at which performance peaked differed according to lens strength. The lenses producing greater levels of blur (around 1.86 D of experienced defocus, and stronger), resulted in slower completion times than those producing less blur, even on the final two runs. These effects can be seen in figures 3 and 5. This indicates that although performance improved and peaked under all blur conditions, the maximum level of performance on our task was still affected by blur after the mazes had apparently been learned quite thoroughly. These results have important implications for models of route learning, indicating that while spatial learning can still occur under fairly extreme levels of spherical defocus, deficits in visual detail still negatively influence visually guided route-learning performance.

Regarding implications for spatial learning under conditions of blur in the real-world, our results show that wayfinding ability exhibits a surprising degree of robustness to blur. The inflection point of the function of blur and performance was not reached until approximately 2 cycles  $\text{deg}^{-1}$ . This implies that it should be possible in principle to undergo similar visually guided route-learning tasks using residual vision nearing the levels of legal blindness limits. Of course, there are multitudinous other factors to consider in mobility training for the visually impaired. Still, we believe that further research could provide useful general guidelines for rehabilitation efforts regarding residual vision and route-learning potential.



**Figure 5.** Results from experiment 2. Mean maze completion times for each run under each lens condition. Error bars show  $\pm 1$  SEM.

As mentioned in section 1, some previous studies of visually impaired individuals have suggested that visual acuity is not a primary determinant of their navigational performance. Our results suggest a reason why this might be so. Specifically, we show that visually guided route learning is quite robust to visual acuity losses, so that impairment of this faculty might not affect route-learning ability as strongly as others, such as contrast sensitivity and visual-field losses. An advantage of the current study over previous ones, which primarily examined individuals with a range of visual impairments (eg Kuyk et al 1998a, 1998b), is that we examined visual acuity in isolation and parametrically. This permitted us to give a quantitative estimate as to the point where visual acuity losses per se produce impairment.

In terms of vision-enhancement systems, such as NVGs, our results suggest that any impairment they induce in navigation ability is primarily due to factors other than the quantisation effect they produce. This is because NVGs reduce visual acuity to between 20/30 and 20/60 (Macuda et al 2005), which is far less blur than the point at which we see significant impairments to route-learning performance (around 20/110 to 20/130). Thus, it seems likely that it is the visual-field limitations or scintillating motion noise that NVGs produce (Gauthier et al 2008; Macuda et al 2005), or some combination of these and other factors, that contributes to spatial positioning difficulties while wearing them. In research on how NVGs affect spatial knowledge, their effects in a global fashion have typically been examined. That is, participants wear NVGs and experience all of the visual limitations they impose (eg Gauthier et al 2008; Macuda et al 2005). Our research suggests that examining the various forms of visual component limitations in isolation would provide useful feedback on how to design better systems and how to compensate for the limitations imposed by current systems.

In examining our results, it should be evident that the threshold values measured here are unlikely to hold precisely for all navigation tasks. In the current studies we have examined visually guided route-learning performance under very precise and simple stimulus and task conditions. Alterations in either of these areas would likely change the overall threshold level. For instance, the inclusion of explicit visual landmarks could very well alter the results, as could employing a more immersive virtual environment. Similar variations relative to basic thresholds are seen in research on SF effects in visual-recognition tasks (Collin 2006; Collin and McMullen 2005; Ruiz-Soler and Beltran 2006). However, such variations are modest and tend to centre around a central basic threshold. We anticipate such findings with visually guided route-learning tasks. We are

currently running and planning a series of further studies to examine the effects of such manipulations on the function of visually guided route-learning performance and SF cut-off.

Although using a virtual environment has a number of advantages (Fortenbaugh et al 2007), it also presents several limitations that must be considered in interpreting our findings. For instance, the type of virtual environment employed here does not allow for stereoscopic depth to be experienced. Additionally, proprioceptive and vestibular information is not available to participants (for an explanation of the importance of body-based information in mobility tasks, see Ruddle and Lessels 2006, 2009). Finally, the blur induced by the lenses in our task is imposed relative to the flat two-dimensional presentation of the three-dimensional maze environment, and does not faithfully reflect the way that more distant objects would be affected by defocus in a real-world setting. We are currently planning studies to examine similar questions in real-world human scale Hebb–Williams navigation environments. These future studies will complement the present one by allowing us to overcome the limitations imposed by the virtual environment.

One goal of the present study was to quantify the low-pass SF threshold at which visually guided route learning becomes impaired. To do this, we filtered spatial frequencies by applying spherical defocus via lenses of varying dioptric strengths. While this has approximately the same effect as applying more traditional digital image processing techniques (eg applying a Butterworth filter to the Fourier transform), it does create some differences. For instance, as Akutsu et al (2000) note, the modulation transfer function of a spherically defocused imaging system has a number of lobes below the first zero crossing. Some of these are negative, producing phase reversals. In approximating the SF cut-off produced by our lenses, we ignored these lobes and simply calculated the 50% gain point of the function. While this means that our SF cut-offs are only approximations, it should be noted that Akutsu et al found no difference in visual acuity when they excluded these additional lobes. We therefore believe that our calculated threshold of approximately  $2 \text{ cycles deg}^{-1}$  is a reasonably accurate measure of the point at which visually guided route learning becomes impaired. Future studies, in which the images of the mazes will be digitally filtered in real-time, are planned to confirm this.

In conclusion, we have provided some of the first systematic examinations of SF limitations on visually guided route-learning performance in new environments. Our findings indicate that the function of low-pass SF cut-off and visually guided route-learning performance are nonlinear, following a sigmoidal pattern characteristic of a behavioural threshold. This threshold is quite low on the spectrum, around  $2 \text{ cycles deg}^{-1}$ , indicating that visually guided route-learning ability is fairly robust to blur. Our results also demonstrate that while visually guided route-learning performance is improved with increased exposure to the environment under all levels of blur, absolute performance is ultimately affected. That is, stronger levels of blur produce slower absolute times to complete the task once learning has occurred. These findings have important implications for models of wayfinding, specifically route learning, as well as real-world situations in which individuals must navigate under conditions of visual blur.

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**Appendix**

**Computer/Video Game Usage Questionnaire**

The intent of this questionnaire is to determine your experience and exposure to computer and video games throughout your lifetime. It is important that you answer each question as truthfully as you can and to the best of your knowledge as this information will be used as part of the study. Please note that all information provided is completely confidential and only accessible by the researchers.

Name: .....

Gender: .....

Age: .....

Handedness: .....

Please answer each question to the best of your knowledge, using educational guessing as necessary. Circle only one response for each question.

**Question 1.**

Between the ages of **7 and 12**, how many hours per week **on average** did you play computer and/or video games?

..... hours

**Question 2.**

Of the hours responded in **Question 1**, how many of these hours **on average** were spent playing first-person shooter games (ex. Wolfenstein, Doom, Halo, Quake, etc.)?

..... hours

**Question 3.**

Between the ages of **13 and 18**, how many hours per week **on average** did you play computer and/or video games?

..... hours

**Question 4.**

Of the hours responded in **Question 3**, how many of these hours **on average** were spent playing first-person shooter games (ex. Wolfenstein, Doom, Halo, Quake, etc.)?

..... hours

**Question 5.**

Since (and including) the age of **19**, how many hours per week **on average** did you play computer and/or video games?

..... hours

**Question 6.**

Of the hours responded in **Question 5**, how many of these hours **on average** were spent playing first-person shooter games (ex. Wolfenstein, Doom, Halo, Quake, etc.)?

..... hours

**Question 7.**

If you have any general comments, please describe them here:

.....  
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Thank you for taking the time to fill in this questionnaire.



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