

1 **Title:** Environmental anchoring of grid-like representations minimizes
2 spatial uncertainty during navigation

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17 **Summary**

18 Minimizing spatial uncertainty is essential for navigation, but the neural mechanisms remain
19 elusive. Here we combine predictions of a simulated grid cell system with behavioural and
20 fMRI measures in humans during virtual navigation. First, we showed that polarising cues
21 produce anisotropy in motion parallax. Secondly, we simulated entorhinal grid cells in an
22 environment with anisotropic information and found that self-location is decoded best when
23 grid-patterns are aligned with the axis of greatest information. Thirdly, when exposing human
24 participants to polarised virtual reality environments, we found that navigation performance is
25 anisotropic, in line with the use of parallax. Eye movements showed that participants
26 preferentially viewed polarising cues, which correlated with navigation performance. Finally,
27 using fMRI we found that the orientation of grid-cell-like representations in entorhinal cortex
28 anchored to the environmental axis of greatest parallax information, orthogonal to the
29 polarisation axis. In sum, we demonstrate a crucial role of the entorhinal grid system in
30 reducing uncertainty in representations of self-location and find evidence for adaptive spatial
31 computations underlying entorhinal representations in service of optimal navigation.

32

33 **Keywords:** spatial navigation; grid cells; computational modeling; virtual reality; fMRI; eye-
34 tracking.

35

36 INTRODUCTION

37 Accurate navigation is a daily challenge for humans and other animals alike. In order to self-
38 localise an agent must integrate incomplete and uncertain information regarding its position
39 and motion. In the brain, entorhinal grid cells are thought to play a central role in this
40 process¹⁻⁶ – appearing to provide an efficient representation of self-location updated on the
41 basis of self-motion and the proximity to salient cues. However, while sensory
42 representations - such as those found in the visual cortex - are known to adapt in response
43 to varying levels of uncertainty^{7,8}, it is unknown whether spatial representations in the medial
44 temporal lobes respond similarly.

45
46 In rodents, the regular triangular firing-patterns of grid cells can be heavily distorted by
47 environmental geometry - tending to align to walls of rectangular enclosures^{9,10}. It becomes
48 fragmented in hair-pin mazes and distorted in trapezoidal environments^{10,11}, which translates
49 into systematic memory distortions in humans¹². Human entorhinal fMRI- and iEEG activity
50 during virtual navigation is modulated by movement direction. This modulation shows six-fold
51 rotational (hexadirectional) symmetry that has been proposed as a population signal of grid
52 cells (i.e. grid-cell-like representations)¹³⁻²⁰. These grid-cell-like representations are present
53 also during visual exploration and anchor to square boundaries^{16,17}. Similar activity patterns
54 have been observed in monkeys during visual tasks²¹.

55
56 Currently, it is unclear whether these distortions are maladaptive - a failed attempt to
57 generate a regular grid, which might conceivably result in navigational errors²². However, an
58 alternative explanation could be that the irregularities confer an advantage, supporting more
59 accurate self-localisation than regular grid-patterns would. Indeed, theoretical considerations
60 suggest that the transient expansion in grid scale observed when animals are exposed to
61 novel enclosures²³ may be a strategy to minimise decoding errors in unfamiliar and hence
62 uncertain environments². Plausibly similar adaptive processes would generate altered grid-
63 patterns in response to asymmetries or local variability in the availability of reliable spatial
64 cues.

65
66 Here, we test if polarised spatial cues – providing anisotropic motion parallax information
67 during self-motion - systematically alter the configuration of grid-like representations in a way
68 that is consistent with the minimisation of decoding errors. To this end, we employed a
69 simulated grid cell system to make specific predictions about the optimal orientation of grid-
70 patterns under conditions of asymmetric spatial information. In turn, we tested these
71 predictions against the orientation of human grid-cell-like representations monitored while
72 human subjects performed a virtual navigation task. Eye-tracking data and behavioural

73 performance measures were used to assess the participants' use of spatial cues and their
74 ability to navigate accurately within the VR.

75

76 **RESULTS**

77 **Impact of environmental geometry on grid pattern may be adaptive**

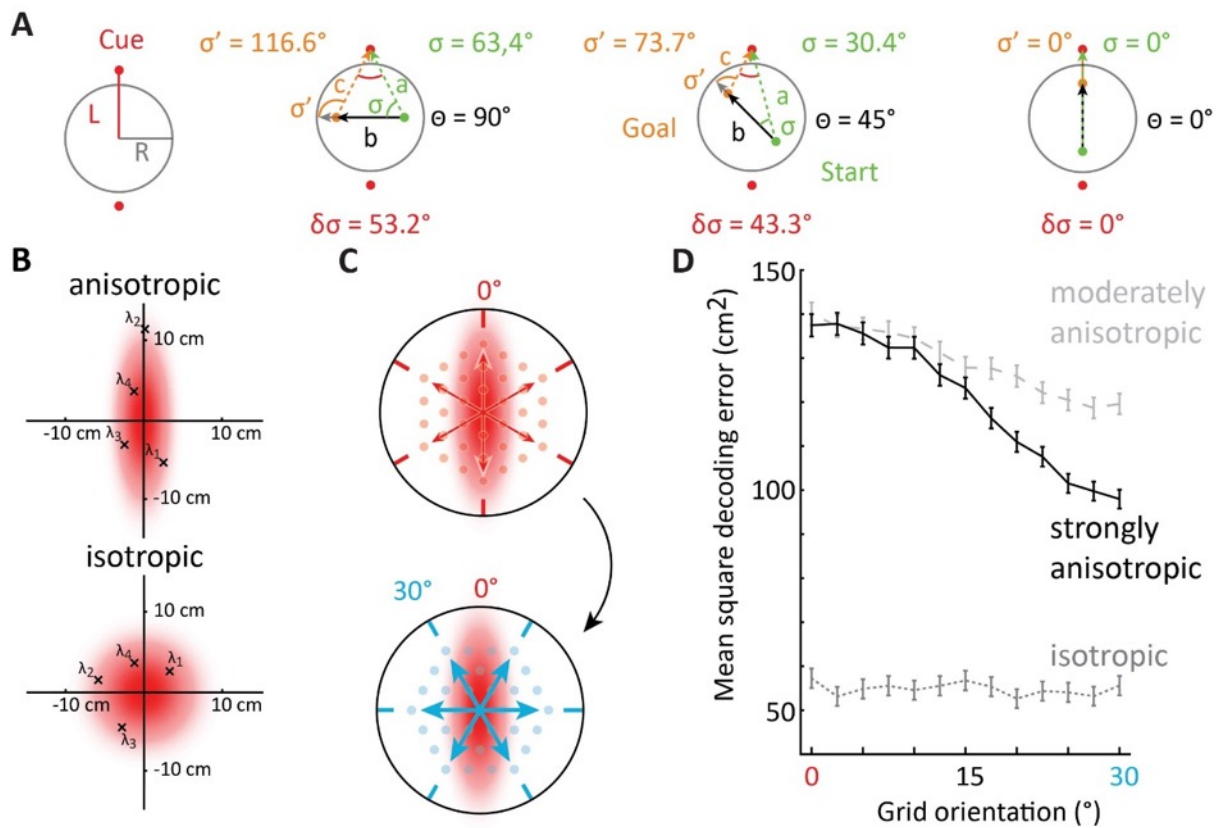
78 Computational simulations suggest that grid cell firing patterns can partially mitigate the
79 effects of increased spatial uncertainty by increasing in scale² – an effect observed
80 empirically in novel environments²³. We build on this existing framework^{2,4}, inquiring how
81 position decoding using a population of grid cells with coherent orientation is affected by
82 anisotropy in spatial uncertainty (random displacement of each grid pattern along a cardinal
83 axis). Grid cell ensembles with an orientation offset at 0 to 30° relative to the axis of greater
84 uncertainty were simulated (in a six-fold rotational system 30° is the greatest possible
85 offset).

86

87 The simulations (see Materials and Methods) demonstrated a substantial difference in the
88 accuracy with which self-location can be decoded depending on the orientation of the grid
89 pattern relative to the axis of greatest uncertainty. Specifically, the most accurate
90 representation of position was obtained when the grid population was oriented at 30° to the
91 axis - equivalent to being fully misaligned to the axis defined by the spatial cues; Figure 1C,
92 Figure 1 – figure supplement 1-3). Decreasing the anisotropy in spatial uncertainty
93 diminished this effect, until no directional benefit was apparent for isotropic uncertainty – a
94 spherical noise distributions (Figure 1 and Figure 1 – figure supplement 1). In further control
95 experiments, we varied grid scale, firing rate, and the number of grid modules – the optimal
96 grid orientation relative to an axis of uncertainty remained consistent (Figure 1 – figure
97 supplement 2). Similarly, in the case of less plausible, higher-order noise distributions with
98 multiple peaks, an optimal grid orientation was only present if the alignment of the grid
99 pattern and the noise distribution could be reduced through rotation. This was the case for a
100 six-leaf distribution, but not for a four-leaf distribution (Figure 1 – figure supplement 3).

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104 **Figure 1. Spatial information is anisotropic and affects optimal self-localisation using grid cells.** **A** Spatial
 105 information during movement in polarised environments is anisotropic. Left: schematic of arena with radius R ,
 106 and polarising cues at distance L . Right: three example paths in different directions and through the centre are
 107 shown (black arrows at angle θ ; Path lengths are equal to distance of the cue to the centre). The change in cue
 108 direction from the observer's heading ($\delta\sigma$) is maximal on paths perpendicular to the polarisation axis (note: this is
 109 also the case on average if paths are not centred on the middle but distributed evenly throughout the
 110 environment). **B-D** We simulated decoding of position estimates from the activity of grid cell ensembles with
 111 patterns oriented at different angles relative to the axis of lowest spatial certainty. Note that the axis of lowest
 112 spatial certainty in **A** is the polarisation axis formed by the two cues, because angular change is smallest and
 113 triangulation errors are largest along it. Uncertainty in spatial information for the simulations of position decoding
 114 using grid cells was introduced by adding Gaussian errors to the true position input. These errors were generated
 115 independently for each module of grid cells. Anisotropy was created by separately varying the standard
 116 deviations of the error in two orthogonal axes. **B** illustrates an example: the subject's actual location is at the
 117 origin; red shading indicates a two-dimensional probability density distribution for error generation, with either
 118 different or equal standard deviations in each axis (anisotropic and isotropic, respectively); and crosses indicate
 119 four independently generated noisy position estimates, drawn from this distribution and be input to each of the
 120 grid cell system's four modules. **C** Schematic illustration of two grid orientations either aligned with the
 121 uncertainty axis (left panel, arrows indicate hexadirectional orientations associated with a grid), or rotated 30°
 122 (right panel). The number of depicted grid fields differ only for illustration purpose. **D** Position decoding error,
 123 defined as the mean maximum-likelihood estimate square error (MMLE; cm^2), was largest when one grid axis
 124 was aligned at 0° relative to the axis of lowest spatial certainty (as shown in panel **B**, top). No optimal grid
 125 orientation was present in the isotropic condition. Solid black line: 'strongly anisotropic', errors with s.d. 5cm and
 126 0cm; dashed light grey line: 'moderately anisotropic', 5cm and 1.67cm; dotted medium grey line: 'isotropic',

127 3.33cm in all directions. Grid orientation is defined as the minimal angular offset of a grid axis from the axis of
128 greater uncertainty (this is analogous to hexadirectional offset of entorhinal fMRI activity described below). Error
129 bars indicate 95% confidence interval (n=150,000).

130

131 **Motion parallax is maximal during movement perpendicular to polarising cues**

132 To investigate the effects of uncertainty on grid cells and navigation, we first sought to
133 generate a virtual environment characterised by anisotropic spatial information. Because
134 motion parallax - the apparent change in bearing to stationary points - is a major source of
135 spatial information during movement²⁴, we reasoned that an enclosure with cues distributed
136 along a single axis would exhibit the desired asymmetry. Below we characterise an
137 anisotropy of such angular change in polarised environments.

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139 Suppose we have a circular arena of radius R centred on the origin, with a polarising cue at
140 distance L (Figure 1A). As an agent moves on a straight path b , we are interested in the
141 angle σ from the agent's heading to the cue, and how it changes when the agent moves. If
142 the cue is within the arena ($L < R$), then the maximal change in angle (π radians) occurs when
143 the agent moves towards and through the cue. If the cue is outside the arena ($L > R$), and the
144 length of the path is very short (i.e. in the limit $b \rightarrow 0$) we can calculate the change in angle
145 $\delta\sigma$ to the cue (see Figure 1A, middle panel for example illustration with a longer path):

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$$147 \quad \frac{\delta\sigma}{b} = \frac{\sin \sigma}{a} \quad (1)$$

148

149 If the agent is on the x axis (i.e. $y = 0$) then we see that $\delta\sigma$ is proportional to $\sin \sigma$ which is
150 maximal for paths at $\theta = \frac{\pi}{2}$, i.e. movements perpendicular (90°) to the cue.

151 Hence, spatial information during movement is not isotropic across directions (this
152 conclusion holds on average for the entire arena). Specifically, angular change is maximal
153 during movement perpendicular to polarising cues. Spatial computations, such as Euclidean
154 triangulation, benefit from this parallax information and become more noise resilient (Figure
155 1 – figure supplement 4-6).

156

157 To corroborate this analysis, we conducted biologically inspired simulations of Euclidean
158 triangulation in polarised environments (see Methods). As expected, the impact of spatial
159 uncertainty was minimised for movement perpendicular to the polarisation axis (Figure 1 –
160 figure supplement 4-6; two-sided Wilcoxon signed-rank test: $Z = 1026.42$, $p < 0.001$). Results
161 were robust within a plausible range of parameters.

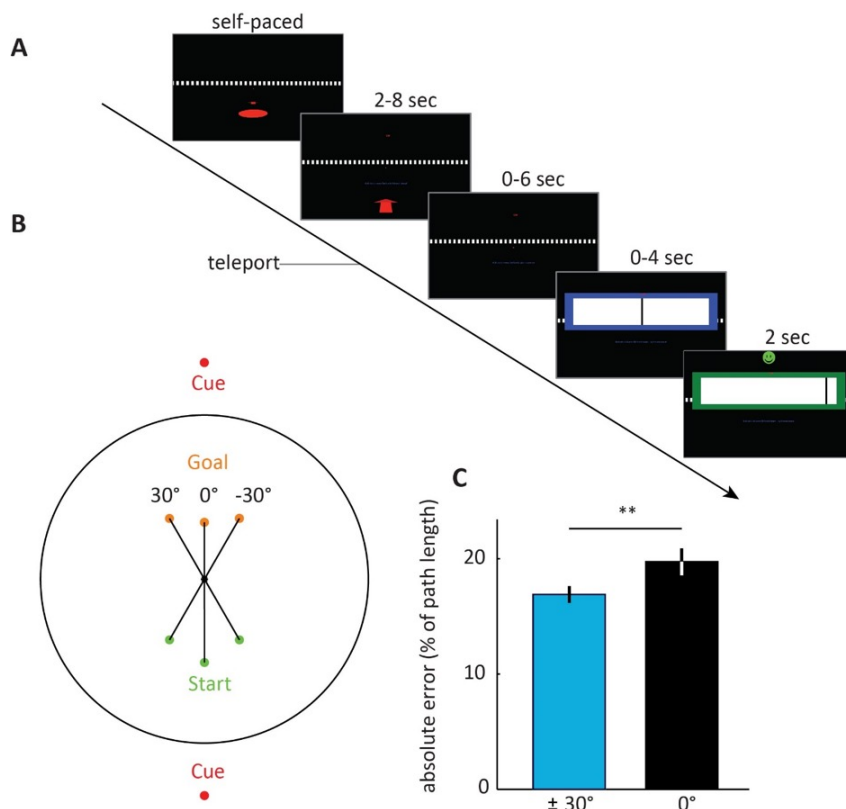
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163 Hence, in a circular environment polarised by two cues, the axis of greatest uncertainty
164 corresponds to movement parallel to the axis defined by the cues. Thus, we would expect to
165 observe larger errors in spatial memory responses in this direction than perpendicular to it.
166 Conversely, to minimise positional errors, grid-patterns should orient to lie perpendicular to
167 the polarisation axis.

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169 **Effects of motion parallax on behavioural distance estimation**

170 To test if participants can use anisotropic parallax information to improve distance estimates,
171 we conducted a behavioural distance estimation task (N=20). In a sparse environment
172 (Figure 2A, Figure 2 – figure supplement 1) polarised by two cues defining an axis,
173 participants freely navigated to a start location. There they could initiate forward teleportation
174 along one of three directions (-30°, 0° and +30° relative to the polarisation axis; Angles < 90°
175 were chosen to allow testing of many distances with limited field-of-view, see Materials and
176 Methods; Figure 2B; Figure 2 – figure supplement 1). At the goal location they gave an
177 estimate of the traversed distance (Figure 2A, see Materials and Methods). As predicted,
178 performance was most accurate when motion parallax was present. That is, when
179 participants moved ±30° oblique to the polarisation axis, as opposed to along it. Figure 2C,
180 absolute error, paired, two-sided t-test N=20, $T_{(19)} = 2.7$, $p=0.007$; Figure 2 – figure
181 supplement 2, mean error, $T_{(19)} = 5.47$, $p<0.001$).



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183 **Figure 2. Behavioural experiment - distance estimation is most accurate on oblique paths.** A Trial event
184 sequence. Following a familiarisation phase, participants navigated to a start location (indicated by the red circle

185 and arrow) and initiated teleportation in a given direction, either along a polarisation axis or at $\pm 30^\circ$ offset, see B
186 and Figure 2– figure supplement 1. Teleportation distance was experimentally manipulated, and participants
187 gave a distance estimate at the goal location by sliding a response bar (black slider in blue box). The cue was
188 visible both at the start and the goal location (small red dot at eye height, in this example trial shown at the
189 direction the arrow is pointing). Subsequently, participants received feedback. **B** Schematic of the three possible
190 path angles shown at the same distance. Path distance varied from trial to trial (see Materials and Methods).
191 Note that no boundary was present. The black circle only illustrates an analogy to the arena environments used
192 in the fMRI experiments. Start and goal positions are illustrated by green and orange dots, respectively. **C**
193 Distance estimation was most accurate on oblique paths, consistent with anisotropy of spatial information. Error
194 bars show S.E.M. over participants.

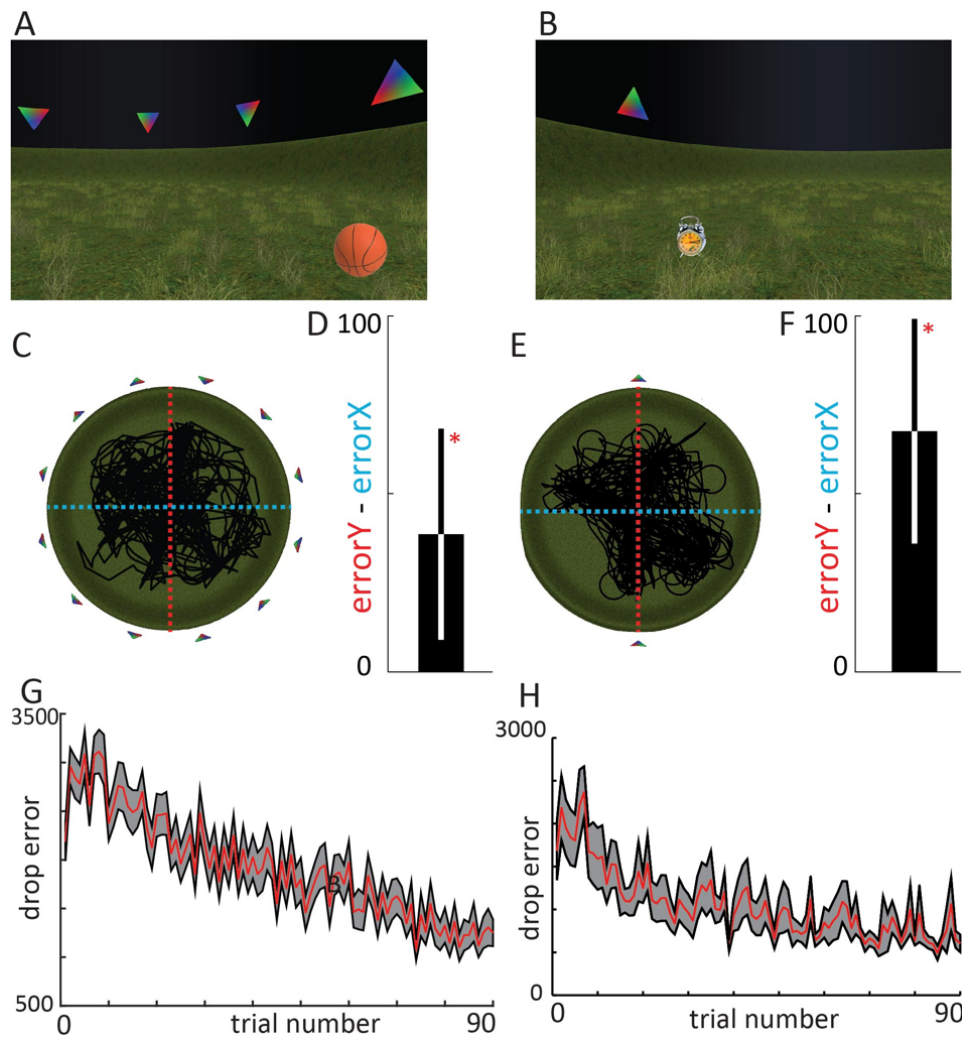
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196 **Polarised environments affect spatial navigation error**

197 In order to test the effects of polarising cues in more naturalistic settings, we conducted
198 navigation tasks in two distinct virtual environments (environment 1: N=50; environment 2
199 N=24). Both environments contained a grassy plain bounded by a cylindrical cliff,
200 surrounded by polarising extra-maze cues (Figure 3). In environment 1, highly similar extra
201 maze cues were visible in all direction (12 in total), but these changed orientation at two
202 opposing points. These inversion points constituted a polarisation axis. A subset of
203 participants that navigated in environment 1 underwent concurrent fMRI scanning (fMRI
204 experiment 1; N=26), while another subset underwent concurrent eye tracking (eye tracking
205 experiment; N=34). Environment 2 was more clearly polarised by a single cue on either side
206 (see Figure 3 and Materials and Methods), with participants undergoing concurrent fMRI
207 scanning (fMRI experiment 2; N=24). In each environment, participants performed a
208 continuous object-location memory task^{13,19} with 6 or 4 object-location associations (see
209 Materials and Methods). Each trial comprised navigating to a target location - participants
210 were able to move forward and rotate but not move backward - giving a response, and
211 receiving feedback. This task was interrupted by occasional inter-trial-intervals when a
212 fixation cross was presented on a grey screen for 2 seconds (on average after every third
213 trial; range: 2-4). Object identity and location was randomised across participants (see
214 Materials and Methods).

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218 **Figure 3. Spatial memory performance is anisotropic.** **Top** First-person view **A** environment 1 (used in fMRI
 219 experiment 1, and the eye-tracking experiment), **B** environment 2 (used in fMRI experiment 2). **C, E** aerial view.
 220 Human participants performed a free-navigation, object-location memory task (one example object shown on
 221 grassy plane, see Materials and Methods). In environment 1 an implicit polarisation axis was defined through the
 222 configuration of cues, i.e. the switch between upright and downward triangles. environment 2, an explicit
 223 polarisation axis was defined with two triangular cues alone. Black lines in aerial view show the paths of
 224 exemplary participants. Red dashed line indicates the polarisation axis (Y dimension), whereas the cyan dashed
 225 line indicates the orthogonal X dimension. **D, F** Bars show the median difference in spatial memory performance
 226 on the Y axis (i.e. the polarisation axis) versus the X axis. To avoid potential bias, we matched the number of
 227 trials in which participants faced (or moved) parallel and perpendicular to the polarisation axis ($\pm 45^\circ$). Spatial
 228 memory performance was anisotropic, with larger errors along the polarisation axis in both environments, which
 229 corroborates the theoretical predictions of an anisotropy in spatial information (Equation 1, Figure 1 and Figure 1
 230 – figure supplement 4). **Bottom** Error bars show S.E.M. over participants.

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232 Despite a relatively sparse environment, participants successfully learnt the object locations
 233 (Figure 3 – figure supplement 1). To avoid potential bias of the anisotropy measure due to
 234 the limitation of navigating using only three buttons, we matched the number of trials in
 235 which participants faced (or moved) parallel (y-axis) and perpendicular (x-axis) to the

236 polarisation axis $\pm 45^\circ$ at the time of the spatial response (median difference in number of
237 trials facing Y - number of trials facing X: environment 1 = 2; environment 2 = 16). We tested
238 if participants' spatial responses were more accurate when given perpendicular to the
239 polarisation axes than in parallel with it, as predicted by the anisotropy in angular change
240 information (Figure 3). To this end, for environment 1, we employed a linear mixed-effects
241 regression model using the lmer function from the lme4 statistics package²⁵ implemented in
242 R 3.5.1 (R Core Team, 2018). As fixed effects, we tested the intercept of the effect of the
243 median X error on the median Y error. As random effects, we used intercepts for the factor
244 experiment with two levels (fMRI experiment 1 and eye tracking experiment; One-sided test;
245 $T_{(57)} = 1.812$, $p = 0.0376$; Median percentage of X error relative to Y error = 3.8 %).

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247 For environment 2, we employed a paired one-sided t-test ($T_{(23)} = 2.1441$; $p = 0.02141$;
248 Median percentage of X error relative to Y error = -15.2%). Participants' spatial memory
249 performance in both environments hence indicated that movement directions parallel to the
250 polarisation axes were associated with low spatial certainty. Next, we asked if participants'
251 viewing behaviour would reflect increased exploration of more informative cues.

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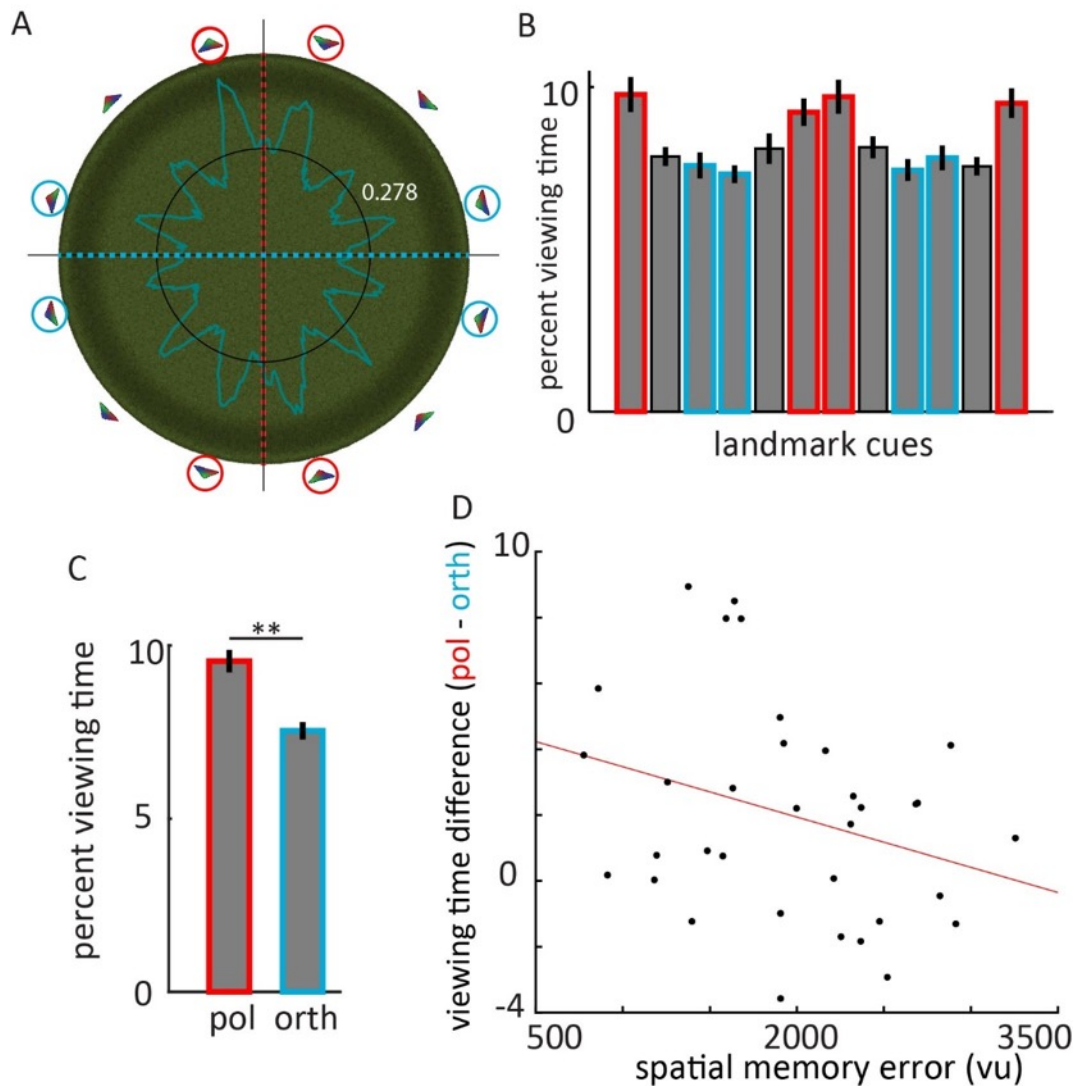
253 **Polarising cues are viewed for longer**

254 We asked next if participant's viewing behaviour would reflect the use of the polarisation
255 axis. Notably, the visual appearance of all cues was matched and cannot explain any
256 potential viewing time differences. We examined these potential differences in viewing times
257 between cues using a repeated-measures ANOVA. Indeed, average percent viewing time
258 differed between cues (Figure 4; $F_{(11)} = 4.98$, $p < 0.0001$, $n = 34$). However, our specific
259 hypothesis was that the configural cues forming the polarisation axis (i.e. two pairs of cues of
260 opposite orientation) were the ones most viewed and informative for navigation behaviour. A
261 one-tailed paired t-test revealed that the configural landmarks were indeed viewed longer
262 than the ones orthogonal to the polarisation axis ($T_{(33)} = 3.60$, $p = 0.0005$). This reliance on
263 polarising cues correlated with spatial memory performance across participants. In
264 particular, the difference in viewing time of polarising cues versus orthogonal cues correlated
265 negatively with participant's mean spatial memory error (Figure 4D. Pearson correlation, one
266 sided, $R = -0.2997$, $P = 0.0425$).

267 The longer viewing times of the polarising cues and the correlation with spatial memory
268 strongly suggests that they were key elements for. If hexadirectional activity as an index of
269 grid-cell-like representations would exhibit a preferred orientation orthogonal to the
270 polarisation axis, this would provide evidence for an adaptive nature of the impact of
271 environmental geometry on the grid pattern.

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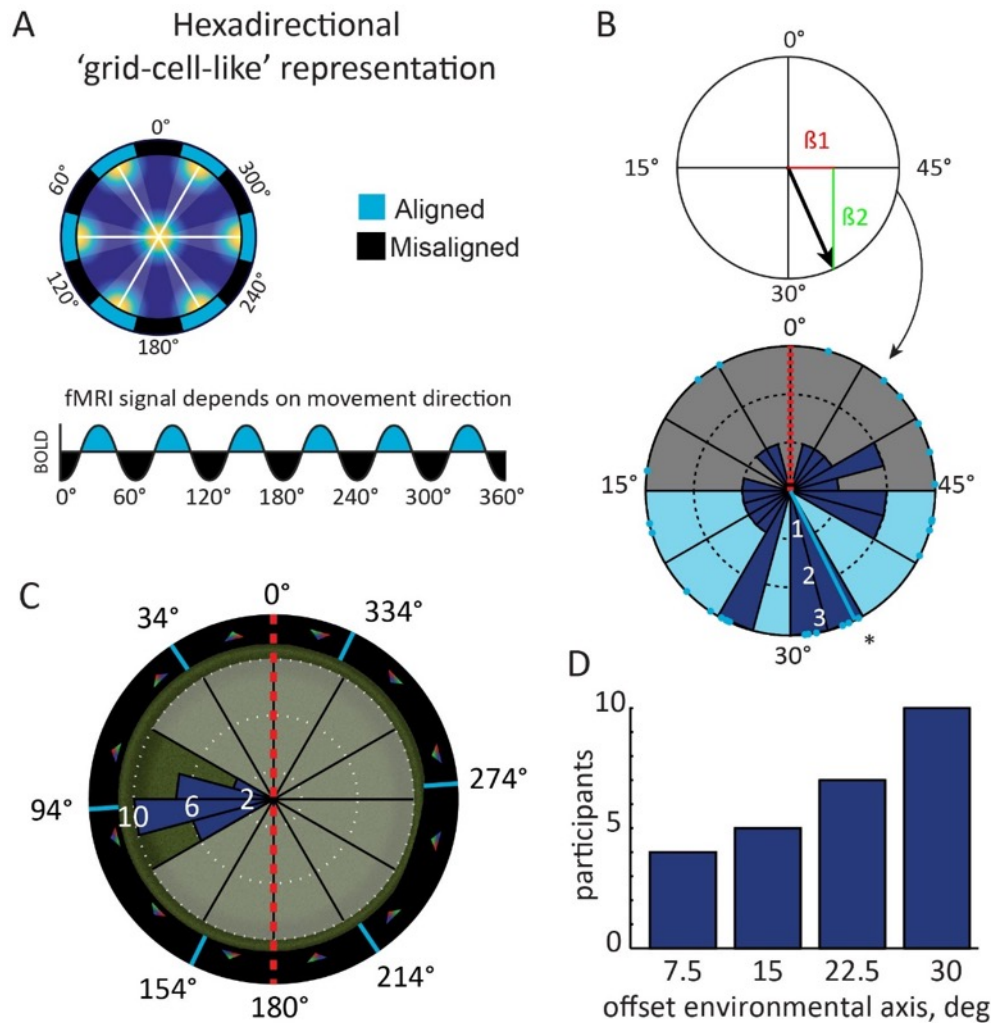
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Figure 4. Eye tracking experiment - Participant's behaviour in the '12 cue' environment (used in fMRI experiment 1 and the eye tracking experiment) reflects stronger reliance on the polarising cues. **A** Percent viewing time is plotted for fixations of 360 evenly spaced points on the boundary of the arena defined by the surface of the cues. Black circle: chance level of even distribution of viewing time across all points. Cues marked with red circles constitute the polarisation axis, cues marked with cyan are perpendicular to the polarisation axis. **B** Bars show average percent viewing time in 30° wide bins that were centered on each of the 12 cues. **C** Participants viewed the cues that form the polarisation axis longer than those perpendicular. **D** Spatial memory error correlated with the difference in viewing time of polarising cues versus orthogonal cues. Error bars show S.E.M. over participants.

Grid-cell-like representation orient to misalign with an axis of high spatial uncertainty

To examine how grid-cell-like representations orient in simple polarised environments, we estimated hexadirectional entorhinal activity^{13,15,19} for each participant. In brief, the method takes advantage of a six-fold periodic directional modulation of fMRI activity in entorhinal cortex during virtual movement (see Materials and Methods). First, we estimated individual

291 orientations of hexadirectional entorhinal activity on the first half of the data. These
292 orientations were not randomly distributed, but clustered approximately perpendicular to an
293 axis defined by the configural cues (fMRI experiment 1, Figure 5). The absolute angle to the
294 nearest 'grid axis' was approximately 30°, corresponding to maximum mis-alignment.
295 Circular mean = 34°; Figure 5C-D; N=26, circular V test for deviation from homogeneity
296 perpendicular to the polarisation axis: $V=6.68$, $p=0.032$). Note that low-level visual features
297 were equal in all viewing directions. Second, we performed a whole-brain analysis on the
298 second half of the data. This confirmed that activity in right entorhinal cortex was increased
299 for runs at periods of 60° aligned with the orientation identified from the first half of that data
300 (Figure 6A-D, peak voxel t-test, $T_{(25)}=4.44$, $p=0.034$, small-volume FWE-corrected).
301 Consistent with the presence of grid-cell-like representations, runs aligned versus misaligned
302 show largest activity increase for 6-fold rotational symmetry but not for biologically
303 implausible control models of 5- or 7-fold rotational symmetry (repeated-measures ANOVA:
304 $F(3,25) = 8.3$, $p < 0.001$; Post-hoc, paired t-tests with Holm-Bonferroni correction, * $p<0.05$).
305 No other peaks remained across the cerebrum even at more liberal thresholds ($p<0.001$
306 uncorrected; $T>3.45$) and neither was there a notable circular clustering of hexadirectional
307 activity in 2 control regions (mammillary bodies, which are close to the hippocampal
308 formation: V test: $V=3.33$, $p=0.822$; right, primary visual cortex: V test: $V=0.10$, $p=0.489$; See
309 Materials and Methods).
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313 **Figure 5. Hexadirectional activity in entorhinal cortex aligns perpendicular to the polarisation axis. A**

314 Hypothesis: movement parallel with the axes of grid cells is associated with increased fMRI BOLD signal ^{16,19}; **B**

315 Top: Analysis procedure: the preferred orientation of hexadirectional fMRI activity in the entorhinal cortex was

316 estimated by first fitting a general linear model (GLM) to the data with 60°-periodic sine and cosine regressors.

317 This yields the associated parameter estimates β_1 and β_2 , respectively. The preferred orientation in 60°-space

318 (black arrow) can be derived from β_1 and β_2 (see Materials and Methods). The corresponding preferred

319 orientation of hexadirectional activity in 360°-space can then be deduced. Here, this corresponds to multiples of

320 60° centered on 34° (light blue lines in C) relative to the polarisation axis (red dashed line) at 0°. **B** Bottom:

321 Individual, preferred orientations in 60°-space (light blue dots) in right entorhinal cortex clustered at roughly 30°

322 offset relative to the polarisation axis (red dashed line); mean orientation = 34° (light blue line). **C** Histogram of

323 preferred hexadirectional activity plotted in full circular space (360°). Note that one of the hexadirectional axes

324 (light blue lines) is roughly orthogonal to the polarisation axis (red dashed line), in line with optimal angles for self-

325 localisation (Figure 1D) **D** Absolute angle between nearest axis of hexadirectional activity shown in B and the

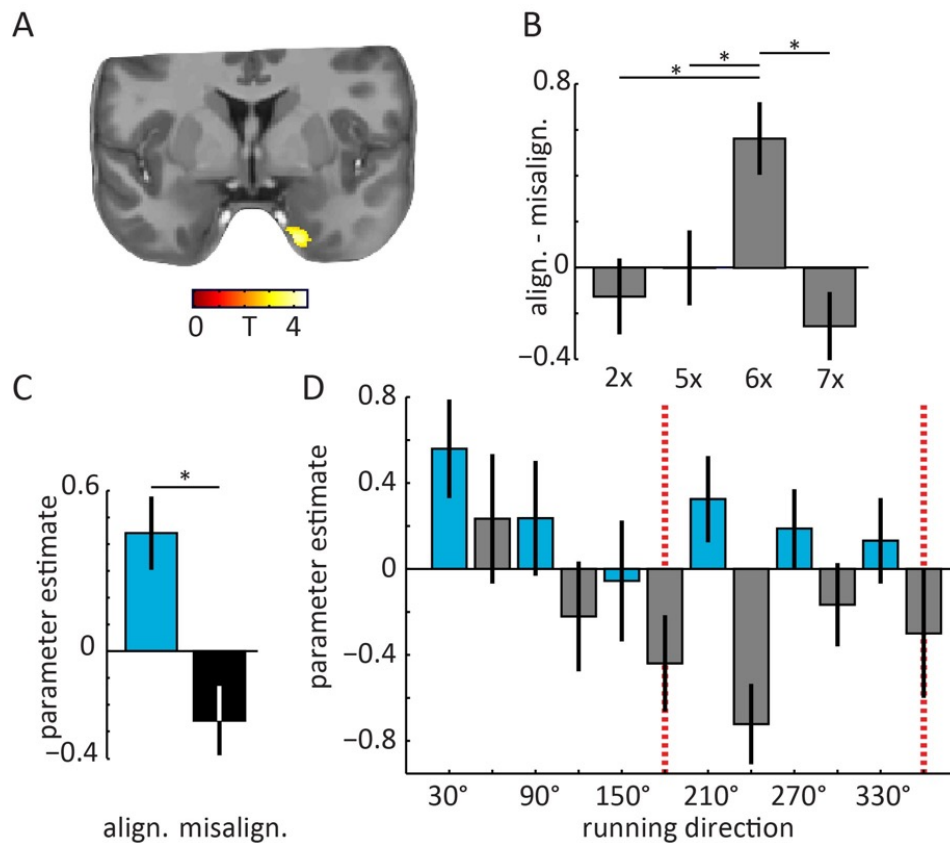
326 polarisation axis illustrate a tendency towards maximal misalignment. Note that the maximum offset is 30° due to

327 the 60° periodicity of hexadirectional activity.

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align. misalign.

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Figure 6 Cross-validation of hexadirectional activity in entorhinal cortex and control models. A A whole-brain cross-validation confirmed that entorhinal activity was increased on runs aligned with the predicted grid (i.e. runs in 30°-wide bins centred on 30°, 90°, 150° etc. indicated by light blue arrows in C and D; see Materials and Methods for details). Peak voxel t-test, $T(25)=4.44$, $p=0.034$, small-volume FWE-corrected). Image is thresholded at $p<0.001$ uncorrected for display purpose. Across the cerebrum no other peaks were observed at this threshold. The T statistic (colour bar) is overlaid on the structural template. **B** In agreement with grid-cell-like representations, runs aligned versus misaligned show largest activity increase for 6-fold (6x) rotational symmetry but not for biologically implausible control models. Next to 5- and 7-fold rotational symmetry, 2-fold symmetry was tested to rule out a direct effect of running parallel to the polarisation axis or not. For all analyses the aligned condition was centered at an angle equivalent to 90° from the polarisation axis (e.g. 30° for 6-fold symmetry). **C** Parameter estimates of runs aligned (light blue, see schematic grid in Figure 1C right panel) and misaligned (black) with the predicted hexadirectional orientation extracted from the peak voxel in A. **D** To examine the influence of different running directions, we plotted the parameter estimates for separate regressors of 12 directional across the entire time-series of fMRI data from the peak-voxel in A. Note the alternating pattern of activity aligned and misaligned. Red dashed lines indicates the polarisation axis. Bars show means and S. E. M. across participants.

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To test if the environmental anchoring depends on the configural cues, we scanned another group of participants in an environment with a non-configural, polarisation axis consisting of only two extra-maze cues (fMRI experiment 2). We estimated individual orientations of hexadirectional activity, and again found that they clustered perpendicular to the polarisation axis (circular mean = 32.28°; Figure 7) replicating the findings from the first experiment

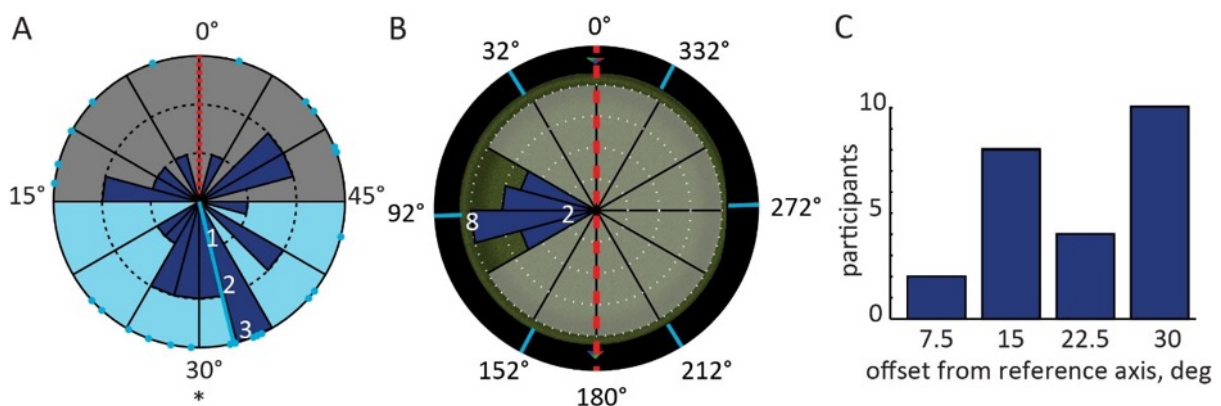
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355 (N=24, circular V test: $V = 5.95$, $p=0.043$; Figure 7). Sampling of running directions could not
356 explain these effects in either experiment (Figure 3 – figure supplement 1). In sum, the
357 results from fMRI experiment 1 and the replication in fMRI experiment 2 provide converging
358 evidence that the preferred orientation of hexadirectional activity in entorhinal cortex
359 depends on navigation-relevant, polarising cues, independent of the specific type of cue
360 (configural or non-configural). The orthogonal arrangement of hexadirectional activity, as an
361 index of grid-cell-like representations, is in agreement with optimal activity patterns of
362 simulated grid cells for self-localisation, suggesting that the impact of environmental
363 geometry on grid cells may be adaptive.
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367 **Figure 7. Environmental effects on hexadirectional activity in fMRI experiment 2.** **A** Preferred
368 hexadirectional activity in 60°-space (light blue dots) in right entorhinal cortex clustered at roughly 30° offset
369 relative to the polarisation axis (mean orientation = 32.28°; light blue line), in line with optimal angles for self-
370 localisation (Figure 1D) **B** Histogram of preferred hexadirectional orientations plotted in full circular space (360°)
371 onto a top-down view of the arena. Note that one of the putative grid axes (light blue lines) is roughly orthogonal
372 to the polarisation axis (red dashed line). **C** Absolute angle between nearest axis of hexadirectional activity
373 shown in B and the polarisation axis. Note that the maximum offset is 30° due to the 60° periodicity of
374 hexadirectional activity.

375

376 DISCUSSION

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378 We examined the effects of polarising cues on spatial navigation behaviour and grid-cell-like
379 representations. We found that estimation of movement distance in a virtual environment
380 was least accurate when participants moved along a polarisation axis and no motion parallax
381 was present. Likewise, spatial memory performance in free-navigation, object-location
382 memory tasks in polarised environments showed relatively larger errors parallel to the
383 polarisation axes (i.e. anisotropy). Eye-tracking recordings indicated that participants viewed
384 polarising cues for longer than other cues, which correlated with their spatial memory
385 performance.

386 To test the theoretical implications of anisotropic spatial information on a system of grid cells,
387 we used biologically inspired simulations. We demonstrate that the representation of self-
388 location is most accurate when grid-patterns align with the axis of highest spatial information.
389 Motion induced parallax is a source of navigation-relevant information^{24,26} and lies at the
390 heart of surveying unknown terrain for the creation of spatial maps. With respect to parallax,
391 the optimal grid-pattern alignment corresponds to grid angles 30° offset from the polarisation
392 axis. fMRI-based estimates of grid-cell-like representations^{13,14,16–19} showed consistent
393 orientations across participants in two independent experiments, yielding the optimal grid
394 orientation for decoding self-location. Taken together, our results provide evidence that the
395 grid system aligns to axes of high spatial information, which suggests that effects of
396 environmental geometry on the grid system are adaptive responses in service of flexible
397 navigation. Furthermore, angular change to stationary cues during self-motion may play a
398 central role in the computations underlying the grid system.

399

400 Could grid-cell-like representations simply follow extra maze cues or object locations? Note
401 that the peaks of hexadirectional activity (grid-cell-like representations) did not correspond to
402 movement directions directly facing a cue in either fMRI experiment. This speaks against a
403 simple sensory ‘anchoring’ of grid-cell-like representations to landmarks in the environment.
404 Importantly, the coherent orientations of grid-cell-like representations can also not be
405 attributed to the presence of objects in each trial, since their locations were randomised
406 across participants and the two fMRI experiments had different numbers of objects.

407

408 Our findings are in agreement with reports showing that entorhinal fMRI activity correlates
409 with Euclidean distance to a goal location²⁷ and the proposal that grid cells might enable
410 goal-directed vector navigation^{1,2,5,28–32}. Interestingly, both angular and distance information
411 that is needed for triangulation can be derived from either visual or proprioceptive and
412 vestibular cues. For example, visually modulated cells in the rat posterior-parietal cortex
413 signal the egocentric cue direction³³ and head-direction cells in the entorhinal cortex and
414 other regions realign to visible cues, but also function without vision and rely on vestibular
415 information³⁴. On the other hand, distance information can be inferred visually from the
416 relative size of objects and cues²⁴ or is based on proprioceptive and timing information
417 during movement, both of which modulate grid cell activity³⁵. Hence, triangulation for
418 navigation could bridge different sensory modalities. Furthermore, it combines egocentric
419 cue directions and distance information to infer map-like, survey representations of the
420 environment, thereby naturally integrating egocentric and allocentric reference frames, which
421 are not mutually exclusive and can work in parallel and across brain regions^{33,36,37}.

422

423 A potential avenue for future studies is to examine the effect of anisotropic spatial
424 uncertainty on rodent grid-cell firing, albeit many animals may be needed to detect such a
425 stochastic effect. It is known that grid cell firing exhibits plasticity, regularising and reorienting
426 incrementally with continued experience of an enclosure (Barry et al., 2007; Barry, Heys, &
427 Hasselmo, 2012; Carpenter et al., 2015; Stensola et al., 2015). Our results suggest that
428 these changes likely optimise the grid-code, allowing for an increasingly accurate
429 representation of self-location. However, the physiological and circuit mechanisms that
430 facilitate and direct this process are currently unknown. Theoretically, a number of authors
431 have considered the impact of noise in grid cell coding of self-location and its implications for
432 the capacity and error-tolerance of the entorhinal spatial representation^{5,41,42}. However, to
433 the best of our knowledge, we have provided the first theoretical and practical account of
434 anisotropic spatial uncertainty on the grid system. It remains to be seen if such asymmetries,
435 which are likely a common feature of the environment⁴³, exert more wide-ranging influences
436 on grid-firing; distorting the grid-pattern or changing the relative scales of different grid
437 modules; or might also impact grid-like coding of non-spatial information. In conclusion, we
438 combined biologically inspired computational models, behavioural tests, eye-tracking and
439 fMRI-based proxy measures of grid-cell-like population activity to test the effects of
440 environmental geometry on the entorhinal grid system. Our results are consistent with an
441 adaptive and flexible role of grid cells in self-localisation and navigation. This opens up the
442 exciting possibility for a deeper understanding of fundamental neural building blocks of
443 cognition and behaviour.
444

445

446 **Materials and Methods**

447

448 ***Simulation of Euclidean triangulation***

449 To test the impact of stochastic fluctuations or noise on triangulation accuracy, we
450 implemented the following simulation in Matlab (2012b, The MathWorks Inc.,
451 Massachusetts). Triangles were formed by two points representing start and end points of a
452 straight path in the horizontal plane (e.g. observer locations at time point 0 and time point 1)
453 and one of two polarising, stationary cues. Triangulation was based on the sine rule
454 according to:

$$455 \quad c = b * \sin(\sigma) / \sin(\delta\sigma) \quad (2)$$

456 where c is the unknown side (distance to the cue at the end point; Figure 1 – figure
457 supplement 4), b the known side (distance travelled), σ the angle to the cue at the start point
458 and $\delta\sigma$ the angular change to the cue between start and end point.

459 Path orientation (azimuth) was varied in steps of 1° , path length remained constant and each
460 path was centred on the origin of the coordinate system. Hence, the start and endpoints of
461 different paths mapped onto a circle. This ensured that the mean distance of different paths
462 to one or multiple cues remained constant. Before the triangulation iterations, random noise
463 was added to the known side and the two distance angles. The error in side length had a
464 mean absolute deviation of roughly 5% the original length (based on typical human distance
465 errors during walking⁴⁴) and was drawn from a Gaussian distribution with mean 0 and a
466 sigma of path length of 15.95. The absolute angular error for a single angle was 5° on
467 average (drawn from a von Mises distribution with mean 0 and a sigma of 6.26) and 15° on
468 average for the absolute cumulative error across all three angles of a triangle. This error rate
469 was based on the mean, absolute angular error observed in humans performing a triangle
470 completion task in virtual reality, which involved pointing to a start location after an outward
471 path with two turns⁴⁵.

472

473 *Triangulation measurements: noise resilience.* Triangulation was repeated for all sides of a
474 triangle using the known base a . If the inferred side was the base (the path), triangulation
475 was repeated with both remaining sides serving as the known side and the two results were
476 then averaged. Dual triangulation for the base was done to avoid biased results due to the
477 selection of any one of the remaining sides. Note that the length of the remaining sides was
478 not constant and changed in opposite directions for different path angles, potentially
479 affecting the noise resilience measure at different path angles. This was not a problem in the
480 reverse case, because the base (side a) had constant length. The triangulation error for the
481 3 sides was computed as the absolute difference in the original side length and the length

482 based on triangulation with noisy input parameters. The 3 error rates were then averaged for
483 further computations and the assessment of noise resilience across paths (Figure 1 – figure
484 supplement 4-6). Furthermore, the distance between the most proximal cue to the centre of
485 each path (the middle of the base of a triangle) was always equal to the length of the path,
486 with the exception of Figure 1 – figure supplement 6 that shows the effects of different path
487 lengths and different noise levels. In other words, usually the path length was half the length
488 of the polarisation axis. Triangulation to additional cues was performed for a given path
489 angle if these were within $\pm 90^\circ$ (determined from the centre of a path) to emulate a limited
490 field-of-view. This meant that cues in only that half of the environment were used for
491 triangulation that was faced on a given path (1 point in Figure 1 – figure supplement 4).

492

493 *Triangulation measurements: triangle quality.* The quality measure for triangle shape
494 (triangle area divided by the sum of squares of side lengths; Figure 1 – figure supplement 4
495 light blue curve) was modified from ⁴⁶ who describe optimization of finite element
496 triangulations in the generation of meshes.

497

498 **Computational models of grid cell systems**

499

500 **Grid cell system model**

501 Spiking activity of a population of grid cells, organised into 4 (except where otherwise
502 specified) discrete modules by spatial period size, was modelled in a two-dimensional
503 circular environment of radius 50cm using Matlab v.8 (Mathworks). Spatial periods or grid
504 scales, λ_i , were determined as a geometric sequence beginning with $\lambda_1 = 25\text{cm}$ and
505 increasing with a scale factor of 1.4 (except where otherwise specified). Tuning curves for
506 each grid scale λ_i were generated with locations of grid nodes specified as a regular
507 triangular grid and expected firing rate at each location determined by a Gaussian
508 distribution centred on the nearest node:

$$509 \quad \alpha_{i,j}(x,y) = f_{max} e^{-\frac{d^2}{2\sigma_i^2}}$$

510 where j specifies a particular cell, d is the distance from (x,y) to the nearest grid node, f_{max}
511 the maximum firing rate (constant across the population; 10Hz except where otherwise
512 specified), σ_i the tuning width of the grid fields ($\sigma_i = 3\lambda_i / (20\sqrt{\log_e 100})$) following ⁴.

513

514 Within each of the 4 modules, $M = 195$ offset tuning curves were distributed in a 13×15
515 rectangular grid via translations of this original tuning curve, as well as adding a random
516 translation common to all grids in the module. This resulted in a total of 1560 grid cells in a
517 system. Grid tuning curves could also be rotated to specified orientations; all grid tuning

518 curves always shared a common orientation. All these transformations were performed using
519 cubic interpolation.

520

521 In each iteration of the model, the true position (x, y) was specified as the centre of the
522 circular environment $(0, 0)$. To model uncertainty, Gaussian noise, with standard deviation
523 varied independently in x and y , was generated separately for each module and added to $(x,$
524 $y)$, to yield a noisy position estimate $(x + \epsilon_{x,i}, y + \epsilon_{y,i})$. Anisotropic uncertainty was produced by
525 independently varying the standard deviations of $\epsilon_{x,i}$ and $\epsilon_{y,i}$ between 0 and 5. All cells within
526 a module therefore received the same noisy position input, but cells in different modules
527 received different input. Thus cell firing rate was now modulated according to $\alpha_i(x + \epsilon_{x,i}, y +$
528 $\epsilon_{y,i})$.

529

530 Higher-order “four-leaf” and “six-leaf” noise distributions were created for control
531 experiments (Figure 1 – figure supplement 3). In polar coordinates, the width (s.d.) of the
532 Gaussian noise distribution along the ray was modulated by a cosine function of the angular
533 coordinate.

534

535 The signal extracted from the grid cell system was the number of spikes, k , generated by
536 each neuron during a finite read-out period, $T = 0.1$ s (the approximate length of a theta
537 cycle) – i.e. a population response $\mathbf{K} = (k_1, \dots, k_N)$. We assume the decoding cannot take the
538 added noise into account in any way, so that given a position x the probability of observing
539 the response \mathbf{K} in time T , following ⁴, is taken to be:

$$540 \quad P(\mathbf{K}|x, y) = \prod \text{Poisson}(k_{i,j}, T\alpha_{i,j}(x, y)) = \prod \frac{(T \times \alpha_{i,j}(x, y))^k}{k!} \times e^{-T\alpha_{i,j}(x, y)}$$

541

542 where $\alpha_{i,j}(x, y)$ is calculated by cubic interpolation from the tuning curve. From the population
543 response \mathbf{K} , we can decode position as the maximum likelihood estimate of (x, y) , that is
544 $\hat{x}, \hat{y}(\mathbf{K})$. Given the initial assumption that all positions within the environment are uniformly
545 likely,

546

$$547 \quad \hat{x}, \hat{y}(\mathbf{K}) = \max P(x, y|\mathbf{K}) = \max P(\mathbf{K}|x, y)$$

548

549 Thus $\hat{x}, \hat{y}(\mathbf{K})$ may be closely approximated by calculating $P(\mathbf{K}|x, y)$ for a sufficiently finely
550 spaced uniform sample of x and y values across the environment, and selecting the values
551 of x and y which yield the greatest $P(\mathbf{K}|x, y)$. We used a spatial bin size of 0.5 cm. Where two
552 or more solutions yielded the same maximal $P(\mathbf{K}|x, y)$ (i.e. decoding was ambiguous), one
553 was randomly selected ^{2,4}.

554

555 *Assessing grid system performance*

556 For each combination of levels of uncertainty in x and in y, we assessed the performance of
557 grid systems whose patterns were orientations to these x-y axes from 0° to 30° at intervals
558 of 2.5°. For each case, five experiments each consisting of 15,000 iterations of this
559 procedure were performed. In each of these five experiments, the square grid across which
560 the environment was sampled to produce tuning curves was set at a different orientation to
561 the environment's Cartesian axes, in order to control for any effect of uneven sampling (the
562 orientations were 0° and 4 orientations randomly selected and then used across all
563 conditions). The results of equivalent pairs of uncertainty levels (e.g. standard deviation
564 respectively in x and y of 0 and 5 cm, and 5 and 0 cm) were combined to total $2 \times 5 \times 75,000$
565 = 150,000 iterations. Using these, accuracy of decoding was assessed via the approximated
566 maximum-likelihood estimate square error, or MMLE, based on the square errors of position
567 decoding:

$$568 \quad MMLE \approx \frac{1}{75000} \sum_{c=1}^{75000} (0 - \hat{x}(K_c))^2 + (0 - \hat{y}(K_c))^2$$

569

570 ***Neuroimaging, behavioural- and eye-tracking experiments***

571

572 ***Participants***

573 *FMRI experiment 1.* 26 participants took part in the study (12 females, age range: 19–36,
574 mean age: 23 years). Materials and Methods were approved by the local research ethics
575 committee (ethics committee University Duisburg-Essen, Germany and CMO region
576 Arnhem-Nijmegen, NL). Written informed consent was obtained from each participant.

577

578 *FMRI experiment 2.* 25 participants took part in this study (11 females, age range: 18-32,
579 mean age: 24 years). One participant was excluded from the analysis due to poor
580 performance (i.e. 55 trials with no location response within 30 seconds of the respective trial,
581 more than a standard deviation above the mean). Materials and Methods were approved by
582 the local research ethics committee (CMO region Arnhem-Nijmegen, NL). Written informed
583 consent was obtained from each participant.

584

585 *Behavioural experiment.* 20 participants (11 females, age range: 18-24, mean age: 20 years)
586 participated in the behavioural experiment. Materials and Methods were approved by the
587 local research ethics committee (CMO region Arnhem-Nijmegen, NL). Written informed
588 consent was obtained from each participant.

589

590 *Eye tracking experiment:* 36 participants (15 females, age range: 18-63, mean age: 26)
591 participated in the experiment. Two participants aborted the experiment early, because of
592 VR-induced nausea, and their data was excluded from all analyses. Materials and Methods
593 were approved by the local research ethics committee (CMO region Arnhem-Nijmegen, NL).
594 Written informed consent was obtained from each participant.

595

596

597 ***FMRI acquisition.***

598 *FMRI experiment 1.* Blood-oxygenation-level-dependent (BOLD) T2*-weighted functional
599 images were acquired on a 7T Siemens MAGNETOM scanner (Siemens Healthcare,
600 Erlangen, Germany) using a three dimensional echo-planar imaging (3D EPI) pulse
601 sequence⁴⁷ with a 32-channel surface coil with the following parameters: TR = 2.7 s, TE =
602 20 ms, flip angle = 14°, voxel size 0.9 × 0.9 × 0.9 mm, field of view (FoV) = 210 mm in each
603 direction, 96 slices, phase encoding acceleration factor = 4, 3D acceleration factor = 2. The
604 scanning session was subdivided into EPI acquisition blocks of 210 volumes each. The
605 majority of participants performed 5 blocks over the course of approximately 55 minutes.
606 Deviations from the 5 blocks in a few participants were due to technical problems or
607 interruptions on behalf of the participants (3 participants had 4 blocks, 2 participants 6
608 blocks). In addition, T1-weighted structural images (MP2RAGE; voxel size: 0.63 mm
609 isotropic) and a field map (gradient echo; voxel size: 1.8 × 1.8 × 2.2 mm³) were acquired.
610 Results of an entirely unrelated, task-independent whole-brain connectivity analysis of data
611 from experiment 1 have been described in a previous report⁴⁸.

612

613 *FMRI experiment 2.* BOLD T2*-weighted functional images were acquired on a 3T Siemens
614 Trio scanner (Siemens Healthcare, Erlangen, Germany) using a three dimensional echo-
615 planar imaging (3D EPI) pulse sequence⁴⁷ with a 32-channel surface coil with the following
616 parameters: TR = 1.8 s, TE = 25 ms, flip angle = 15°, voxel size 2 × 2 × 2 mm, field of view
617 (FoV) = 224 mm in each direction, 64 slices, phase encoding acceleration factor = 2, 3D
618 acceleration factor = 2. Each scanning session consisted of an EPI acquisition block of 1031
619 volumes on average (range: 661-1200), amounting to roughly 31 minutes of scan time. In
620 addition, T1-weighted structural images (MPRAGE; voxel size, 1 mm isotropic; TR, 2.3 s)
621 and a field map (gradient echo; voxel size, 3.5 × 3.5 × 2 mm³) were acquired.

622

623 ***Experimental tasks***

624 *FMRI experiment 1.* Participants freely navigated a 3D virtual reality environment with a
625 modified version of the arena from the studies by Doeller and colleagues^{13,19} (Figure 3A)

626 using a 4-button controller. UnrealEngine2 Runtime software (Epic Games) was used to
627 generate the virtual reality task. Instead of two orthogonal axes that are formed by the walls
628 of square enclosures (as in (Krupic et al., 2015; Stensola et al., 2015)) we opted for the
629 simplest case of a single axis, which was determined by extra-maze cues in a circular arena.
630 We hypothesized that the orientation of grid representations would be coherent across
631 participants, as shown in rats moving through square environments, and that this orientation
632 would be determined by the amount of spatial information obtained on movement paths of
633 such orientation. The environment consisted of a circular arena with 12 extra-maze cues, 6
634 upright and 6 inverted triangles. Two pairs of neighbouring triangles of different orientation
635 comprised the two configural cues on opposite sides of the arena that defined a polarisation
636 axis. To control for possible visual effects on our direction-related analysis, we designed the
637 colour textures for the extra-maze cues in such a way, that the low-level visual features
638 remained equal across cues. Each triangle had a red, green and blue corner, arranged in 1
639 of 6 possible constellations. The arrangement of textures was randomised across
640 participants. Counting one's steps was not possible, because no body parts were visible,
641 and the virtual pitch direction was fixed. Self-motion information such as optic flow induced
642 by the grassy plane was present but did not yield directional information. Participants
643 performed a self-paced object-location memory task that involved collecting and replacing
644 six everyday objects to locations that were randomised across participants. Participants
645 collected each object from its associated location once during an initial phase, by running
646 over it. Navigation was not interrupted during the transitions between trials to enable more
647 natural (ecologically valid) continuous navigation. In each subsequent trial they saw an
648 image (cue) of one of the objects in the upper part of the screen and had to move to the
649 object's associated location and press a button (replace phase). After this response, the
650 object appeared in its associated position and participants collected it again (feedback
651 phase). After an average of 3 trials (range 2-4 trials), a fixation cross on a grey background
652 was presented for 4 seconds (inter-trial-interval, ITI). Object locations were randomised
653 across participants. Since the task was self-paced, the number of trials varied across
654 participants (range: 94-253; mean: 179). Prior to the fMRI experiment, participants
655 performed a similar object-location task with different objects in a different virtual
656 environment outside the scanner to familiarise themselves with the task demands.

657

658 *fMRI experiment 2.* Participants freely navigated the same virtual environment as used in
659 fMRI experiment 1, but with only two extra-maze cues on opposite sides of the arena that
660 defined a polarisation axis (Figure 3A). Participants performed the same object-location
661 memory task described above, except that 4 objects were used instead of 6. Participants
662 performed an average of 117 trials (range: 63-179). Prior to the fMRI experiment,

663 participants performed a similar object-location task with different objects and a different
664 virtual environment outside the scanner to familiarise themselves with the task demands.

665

666 *Behavioural experiment.* Participants freely navigated a virtual reality environment (Figure
667 2A, Figure 2 – figure supplement 1) by using four buttons on a keyboard to move in the four
668 cardinal directions and the mouse to change horizontal viewing direction. The virtual
669 environment was displayed at 1680x1050 pixel resolution and 60 Hz refresh rate
670 approximately 40cm in front of the participants' eyes. They were teleported between varying
671 start and end locations at one of three possible angles and performed a distance estimation
672 task. The environment was a 'pitch black' space with otherwise only three distinguishable
673 elements. First, it included a background consisting of a white dashed line oriented
674 horizontally and projected at infinity. This background provided minimal visual information to
675 perceive rotational movements as well as motion parallax of a cue viewed from different
676 angles. Second, a cue, consisting of a red circle, was displayed vertically on a fixed location.
677 Third, a red circle indicated the start location of each path with an arrow pointing in the
678 direction of the goal location. The rationale behind using a visually sparse environment and
679 teleportation to the goal location was to prevent the use of other distance cues, such as cue
680 size (e.g. patches of grass or a boundary) or an estimate of 'time-of-flight', respectively. This
681 ensured that the change in size of the cue and the change in angle and motion parallax to
682 the cue from start to the end of a path was the sole means by which the distance estimation
683 task could be performed correctly. Prior to the experiment, participants performed a similar
684 distance estimation task in a different virtual environment to familiarise themselves with the
685 task demands. At the beginning of the behavioural experiment, participants were instructed
686 to approach the cue in order to familiarise themselves with its location and distance.

687

688 The trial structure was as follows: Participants were instructed to navigate to the starting
689 point. Once they reached the starting point, their movement was restricted to rotations and
690 the message 'click right mouse button to teleport ahead' was displayed (orientation phase
691 one). Participants could self-initiate teleportation to the goal location by a mouse-click and
692 orienting towards the pointing direction of the arrow, at which point the view was frozen and
693 teleportation commenced 2 seconds later. After teleportation to the goal location, the start
694 location became invisible (the red circle with arrow disappeared), movement remained
695 restricted and only rotations were possible and the message 'click right mouse button to give
696 response' was displayed (orientation phase two). Participants could self-initiate the response
697 phase. Then, a horizontally oriented window was displayed together with the message
698 'indicate distance (left = minimum, right = maximum)' and participants could move the mouse
699 to slide a bar inside the window to indicate how far they thought they were being teleported.

700 The range of possible responses was 0 virtual units (vu) to 6000 vu. For comparison, the
701 arena diameter used in the fMRI studies was 9500 vu for the inner boundary and the length
702 of the polarisation axis (i.e. the distance between opposing, extra-maze cues) was 12064 vu.
703 The range of teleportation distances was 500 vu to 5500 vu (mean = 2742 vu). The
704 response was finalised by another mouse click and subsequently, feedback in the form of
705 smiley faces was given for 2 seconds. The color of a smiley for a response error < 2% of the
706 correct distance was green, light green for an error < 4 %, yellow for an error < 8 %, orange
707 for an error < 16% and red otherwise. During this feedback phase, participants could still
708 move the response bar to see other response-to-feedback mappings (i.e. the smiley
709 associated with a given horizontal pixel location). Once the feedback disappeared,
710 participants were able to freely navigate again. At the beginning of about 50% of trials
711 (determined pseudo-randomly), participants were placed to a point in front of the start
712 location to speed up the experimental procedure (i.e. to reduce navigation time from a goal
713 location to the start location of the subsequent trial) and thereby increase the number of
714 trials. In addition, the orientation phase 1 and 2 were restricted to 6 seconds and the
715 response phase to 4 seconds indicated through the display of a timer. If the time limit was
716 reached, 'Time is up! This trial is invalid' was displayed on a red background and no
717 response was recorded. Teleportation distances and teleportation directions were pseudo-
718 randomly determined on each trial. Teleportation directions were either 0° (approaching the
719 cue on a straight line), -30° or +30°. The location of the cue was at (x = 0 vu, y = 8500 vu)
720 and following the approach of the simulations, all paths were centered on the origin of the
721 coordinate system. However, this would provide a relative advantage to the parallel
722 condition. The size of the cue directly reflects its distance to the observer, which becomes
723 particularly apparent at close proximity. In the -30° and the +30° conditions, the goal location
724 is always further away from the cue compared to the 0° condition at equal teleportation
725 distances. Furthermore, the independent measure (teleportation distance) is linearly
726 associated with goal-to-cue distance only in the 0° condition. To avoid bias due to unequal
727 goal-to-cue distance, we equalized this measure by subtracting the difference across
728 conditions (at equal teleportation distances). In effect, this shifted the teleportation paths in
729 the 0° condition backwards by a given amount (Figure 2B). Due to a limited field-of-view of
730 85°, testing of large path offsets of e.g. 90° was not feasible. The task duration was limited to
731 30 minutes in which participants performed an average of 129 self-paced trials (range: 52-
732 238). Prior to the main task, participants performed a training version of the task in a richer
733 virtual environment with a comparable trial structure where the length of the path was not
734 traversed by teleportation but rather through guided movement.

735

736 *Eye tracking experiment:* During a magnetoencephalography study (MEG; data are subject
737 of an independent report), participants performed the same task in the same virtual
738 environment as in fMRI experiment 1 (i.e. the environment with 12 cues). However, they had
739 to learn the locations of 8, instead of 6 objects. Simultaneously, gaze position and pupil area
740 of the left eye were monitored with an infrared-based Eylink 1000 eye tracking system at
741 1200 hz.

742

743 ***Analysis of eye tracking data***

744 The eye tracking data were converted to screen coordinates. Blinks were removed from the
745 time series based on deviations in pupil area of more than one standard deviation from the
746 mean including 25ms around the blink on- and offsets. After smoothing with a running
747 average kernel of 10 ms and linearly detrending, gaze positions were transformed to
748 velocities expressed as degree visual angle per second. Since gaze velocity profiles differed
749 between translations and rotations during navigation, saccades were detected individually
750 during head rotations and static or translational navigation. During head rotations, saccades
751 were detected using a threshold of 12 times the median-based standard deviation of
752 velocity, during static or translational periods with 6 times the median-based standard
753 deviation of velocity. Saccades shorter than 12 ms were excluded ⁴⁹.

754

755 To examine which cues were looked at most during the experiment, we transformed
756 horizontal gaze positions to degrees visual angle and scaled them linearly to match the
757 physical field of view (36 degrees visual angle) to the virtual field of view (85 degrees virtual
758 visual angle). The resulting virtual degrees visual angles were then combined with the virtual
759 head direction to reconstruct the allocentric viewing direction at each point in time. Since all
760 twelve spatial cues were visible exclusively in the upper visual field, we limited our analysis
761 to gaze positions on the upper half of the screen. Moreover, to account for any potential
762 influence of initial viewing angle on this analysis, we excluded all samples recorded before
763 participants rotated at least 90 virtual degrees away from the starting viewing angle (average
764 time excluded at start of experiment: 15.2 seconds). We then computed the intersection
765 between allocentric gaze and a surface at the radius of the extra-maze cues from the centre
766 of the arena for each point in time as follows. We first generated 360 equally spaced vertices
767 at the radius of the extra-maze cues and computing the vectors between the participant's
768 location and all of these vertices. We then selected the respective vertex with the minimal
769 angular distance to the current allocentric viewing direction. This way, we obtained the
770 position of gaze on the arena border or cues at each given point in time. For each vertex we
771 computed the respective viewing time expressed as percent of all samples obtained for each
772 respective participant to account for differences in experiment duration across participants

773 (Figure 3 – figure supplement 2). To examine whether there were differences in viewing
774 times between cues, we then binned vertices into 30-degree bins centred on the cues and
775 compared average viewing time using a repeated-measures ANOVA. However, our specific
776 hypothesis was that especially the cues forming the polarisation axis should be most
777 informative for the task. To test whether these cues were the ones most viewed, we
778 averaged viewing times for the configural landmarks that comprised the polarisation axis (i.e.
779 two pairs of cues of opposite orientation) and compared it to the average of the four cues
780 orthogonal to the polarisation axis using a one-tailed paired t-test.

781

782 ***FMRI data pre-processing***

783 Image pre-processing and analysis were performed with the Automatic Analysis Toolbox
784 (<https://github.com/rhodricusack/automaticanalysis>). This involved using custom scripts
785 combined with core functions from FSL 5.0.4 (<http://fsl.fmrib.ox.ac.uk/fsl/>) and SPM8
786 (<http://www.fil.ion.ucl.ac.uk/spm>). SPM was used for an iterative functional image
787 realignment and unwarping procedure to estimate movement parameters (three for rotation,
788 three for translation) and to correct images with respect to gradient-field inhomogeneities
789 caused by motion. To improve co-registration and the creation of a group-specific structural
790 and functional template using the Advanced Neuroimaging Toolbox (ANTS;
791 <http://www.picsl.upenn.edu/ANTS/>) structural images were de-noised using an optimised
792 non-local means filter⁵⁰ and mean EPI images were corrected for gradual changes in signal
793 intensity (bias correction) using SPM. Next, structural images were co-registered (based on
794 mutual information) to the functional images using SPM and brain-extraction was performed
795 using FSL. The resulting skull-stripped structural image was segmented into grey matter
796 (GM), white matter (WM) and cerebro-spinal fluid (CSF) voxel masks. Finally, functional
797 images were spatially smoothed with an isotropic 8-mm full-width-half-maximum Gaussian
798 kernel and high-pass filtering with a 128-s cut-off to reduce low-frequency drift.

799

800 ***Physiological artefact correction.***

801 During the 7T-fMRI acquisition of fMRI experiment 1, we recorded the cardiac pulse signal
802 and respiration of participants by means of an MRI compatible pulse oximeter and
803 pneumatic belt (Siemens Healthcare, Erlangen, Germany) at a sampling rate of 50 Hz. In
804 addition, scanner pulses were recorded in an analogue input for synchronisation of fMRI and
805 physiological data at 200 Hz. Due to technical problems, these data were not available for all
806 scanning blocks and participants (average of 2.7 blocks, range 0 to 5 blocks per participant).
807 Physiological artefact correction was performed for fMRI data with available concurrent
808 physiological data. This involved band-pass filtering the pulse data between 20 and 150 bpm
809 (0.3 and 2.5 Hz, respectively) to improve peak detection. Subsequently, RETROICOR was

810 used to create regressors that were fed into the subject-specific fMRI analyses (GLMs) as
811 confound regressors to remove spurious fluctuations. Fluctuations due to cardiac and
812 respiratory phase were each modeled by 6 regressors for sine and cosine Fourier series
813 components extending to the 3rd harmonic. Two additional regressors modeled lower
814 frequency changes in respiration and heart rate with a sliding window analysis following ⁵¹.

815

816 ***Region-of-interest (ROI) definition***

817 Based on our a priori hypothesis ^{13,19}, ROI analyses were performed for the right entorhinal
818 cortex (EC). Right EC ROIs were created on the Montreal Neurological Institute (MNI152) T1
819 template using a probabilistic atlas based on cytoarchitectonic mapping of ten human post-
820 mortem brains ⁵² with FSL 5.0.4 (<http://fsl.fmrib.ox.ac.uk/fsl/>). The probability threshold was
821 conservative (95%) for the estimation of hexadirectional orientations and liberal (0%, i.e.
822 including all voxels with non-zero probability) for the small volume correction of the mask.
823 Thresholded masks were binarised and converted to NiFTI file format and then normalised
824 to the space of the individual functional images via the group-specific EPI template (Figure 5
825 – figure supplement 1) using the Advanced Neuroimaging Toolbox (ANTS;
826 <http://www.picsl.upenn.edu/ANTS/>). SPM was used to reslice the ROI mask dimensions to
827 the EPI dimension, which was again followed by binarisation of the masks. Through the
828 same procedure, a right, primary visual cortex ⁵³ mask (95% threshold) and a mamillary
829 body ⁵⁴ mask (25% threshold) were created for control analyses.

830

831 ***Analysis of fMRI time series***

832 Following pre-processing, fMRI time series were modeled with general linear models
833 (GLMs). The different trial phases of the object-location memory task were modeled with two
834 regressors. One regressor was used for the retrieval phase (replacement of an object) and
835 one for the encoding phase (following the location response, when the object was shown at
836 the correct location and could be collected), both of which were associated with a parametric
837 modulator for spatial memory performance to discount large-error trials. Inter-trial-intervals
838 (presentation of a fixation cross on a grey background) were not explicitly modeled and
839 served as an implicit baseline. The presentation of the object cues and the feedback was
840 modeled with two additional regressors. Furthermore, all GLMs included nuisance
841 regressors, comprising at least 6 movement parameters, 2 regressors for signal fluctuations
842 across white and grey matter voxels and 1 regressor to model time points with frame-wise
843 displacements ⁵⁵ larger than 0.5 mm. In addition, physiological signals have been recorded
844 for a sub-set of participants (see section below for details) which was used to correct for
845 cardiac and respiratory artefacts by means of 14 additional regressors. The main regressors
846 of interest modeled virtual movement periods with two associated parametric modulators

847 (see ‘Analysis of hexadirectional activity’ below for details). Coefficients for each regressor
848 were estimated for each participant using maximum likelihood estimates to account for serial
849 correlations. All parametric modulators were normalized to have zero mean and thus be
850 orthogonal to the un-modulated regressor. Prior to the second-level random effects analysis,
851 the linear contrast images of the regression coefficients underwent nonlinear normalization
852 to the group-specific template brain using ANTS.

853

854 ***Analysis of grid-cell-like representations***

855 The orientation of 6-fold rotational symmetry of entorhinal activity (referred to as
856 ‘hexadirectional activity’ and consistent with grid-cell representations in humans¹⁹) was
857 estimated in participant’s right EC using a quadrature-filter approach on fMRI data during
858 fast movements in all trial phases. Participant’s virtual-navigation fMRI data entered a
859 general linear model (GLM) with two parametric modulators of a movement regressor. These
860 modelled the sine and cosine of running direction $\theta(t)$ in periods of 60° (i.e. $\sin(6*\theta(t))$ and
861 $\cos(6*\theta(t))$) for participant’s 50% fastest movement time points, where grid-cell-like
862 representations can be reliably detected^{13,19}. Multiplication by 6 transformed running
863 direction into 60° periodic space to create regressors sensitive to activation showing a six-
864 fold rotational symmetry in running direction. Activations with six evenly spaced peaks as a
865 function of running direction will produce parameter estimates β_1 and β_2 for the two
866 regressors with large amplitude $\sqrt{\beta_1^2 + \beta_2^2}$. To this end, running direction $\theta(t)$ was
867 arbitrarily aligned to 0° of the coordinate system underlying the virtual reality engine.
868 Participants were not aware of the environmental coordinate system. The relationship
869 between the underlying coordinate system and the polarisation axes (defined by extra-maze
870 cues) differed between fMRI experiment 1 and fMRI experiment 2. The orientation of the
871 polarisation axis (i.e. 0°) had an angular offset from the underlying coordinate system of 15°
872 in fMRI experiment 1 and 90° in fMRI experiment 2. This made it unlikely that an anchoring
873 of grid-cell representations to polarisation axes were due to other factors, such as viewing
874 direction during the start of the experiment, which was -15° in fMRI experiment 1 and -90° in
875 fMRI experiment 2, relative to the visible polarisation axes. Next, the parameter estimates of
876 the two parametric modulators (β_1 and β_2) were extracted from the right EC ROI and used to
877 calculate preferred orientation in 60° space (varying between 0° and 59°). A participant’s
878 mean orientation of hexadirectional activity was defined as $\phi_{60^\circ} = \arctan(\beta_1/\beta_2)$, where β_1 is
879 the averaged beta value for $\sin[6*\theta(t)]$ and β_2 is the averaged beta value for $\cos[6*\theta(t)]$
880 across voxels of the right EC. Dividing by six transformed the mean orientation ϕ_{60° back into
881 standard circular space of 360° for one of the three putative grid axes (the remaining two
882 being 60° and 120° relative to the first).

883

884 Our main research question was if environmental geometry affects the orientation of putative
885 grid-cell representations (see below for a description of the statistical test procedure). To
886 additionally cross-validate effects of entorhinal hexadirectional activity^{13,14,19}, we tested the
887 temporal stability of preferred orientations and their regional specificity in a split-half
888 procedure (Experiment 1). This was done only for experiment 1, because data acquisition
889 was roughly twice as long, participants completed more trials (179 versus 117, on average;
890 two-sample t-test, $T_{(48)}=5.25$, $p<0.001$) and SNR likely higher due to high-field scanning
891 compared to experiment 2, which warranted a sacrifice in sensitivity for the main research
892 question.

893 The procedure involved testing activation differences in the second half of the data with six-
894 fold rotational symmetry that was aligned with the (potentially environmentally determined)
895 hexadirectional activity estimated from the first half of the data. More specifically, the second
896 GLM contained regressors for both 'aligned' and 'misaligned' runs relative to the estimated
897 hexadirectional activity (respectively, this means running directions were either less than \pm
898 15° or more than $\pm 15^\circ$ oriented relative to the nearest axis of hexadirectional activity). As for
899 the estimation procedure, regressors modeling six-fold rotational symmetry captured
900 participant's 50% fastest movement time points. Participants' contrast values (aligned >
901 misaligned) then entered a second level random-effects analysis to test for hexadirectional
902 activity in the entire brain volume acquired. Supra-threshold activation in the right EC would
903 indicate temporal stability and regional specificity of putative grid orientation.

904 Having evaluated temporal stability and regional specificity of the quadrature-filter approach
905 for investigation of grid-cell-like representations in fMRI experiment 1, we decided to
906 maximise statistical power addressing the main research question of environmental effects
907 on hexadirectional activity in fMRI experiment 2.

908

909 ***Analysis of environmental anchoring of hexadirectional activity***

910 We tested environmental anchoring of the hexadirectional activity relative to the polarisation
911 axes by using a V test for circular homogeneity⁵⁶. The V test for circular homogeneity is
912 similar to the Rayleigh test for circular homogeneity and can be used if an a-priori hypothesis
913 of a certain mean direction in a sample of angles is being tested. Due to our hypothesis of a
914 relationship between the orientation of the grid-system and anisotropy in spatial information
915 derived from angular changes to polarising cues, we tested participant's putative grid
916 orientations in 0° - 60° space (Figure 5B and Figure 7A) for the presence of a mean direction
917 aligned 30° off the polarisation axis.

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920

921 **Acknowledgements**

922 CFD's, MN's and TNS's research is supported by the Max Planck Society; the European
923 Research Council (ERC-CoG GEOCOG 724836); the Kavli Foundation, the Centre of
924 Excellence scheme of the Research Council of Norway – Centre for Neural Computation,
925 The Egil and Pauline Braathen and Fred Kavli Centre for Cortical Microcircuits, the National
926 Infrastructure scheme of the Research Council of Norway – NORBRAIN; and the
927 Netherlands Organisation for Scientific Research (NWO-Vidi 452-12-009; NWO-Gravitation
928 024-001-006; NWO-MaGW 406-14-114; NWO-MaGW 406-15-291).

929 CB's, NB's and BWT's research is supported by the Wellcome Trust. NB's research is also
930 supported by the European Research Council. The authors would like to thank A Backus, J
931 Bellmund, P Medendorp and B Milivojevic for useful discussions, A. Vicente-Grabovetsky for
932 help with data analyses, B Somai for help with optimising the behavioural paradigm and C
933 Hutton for support with the physiological noise correction.

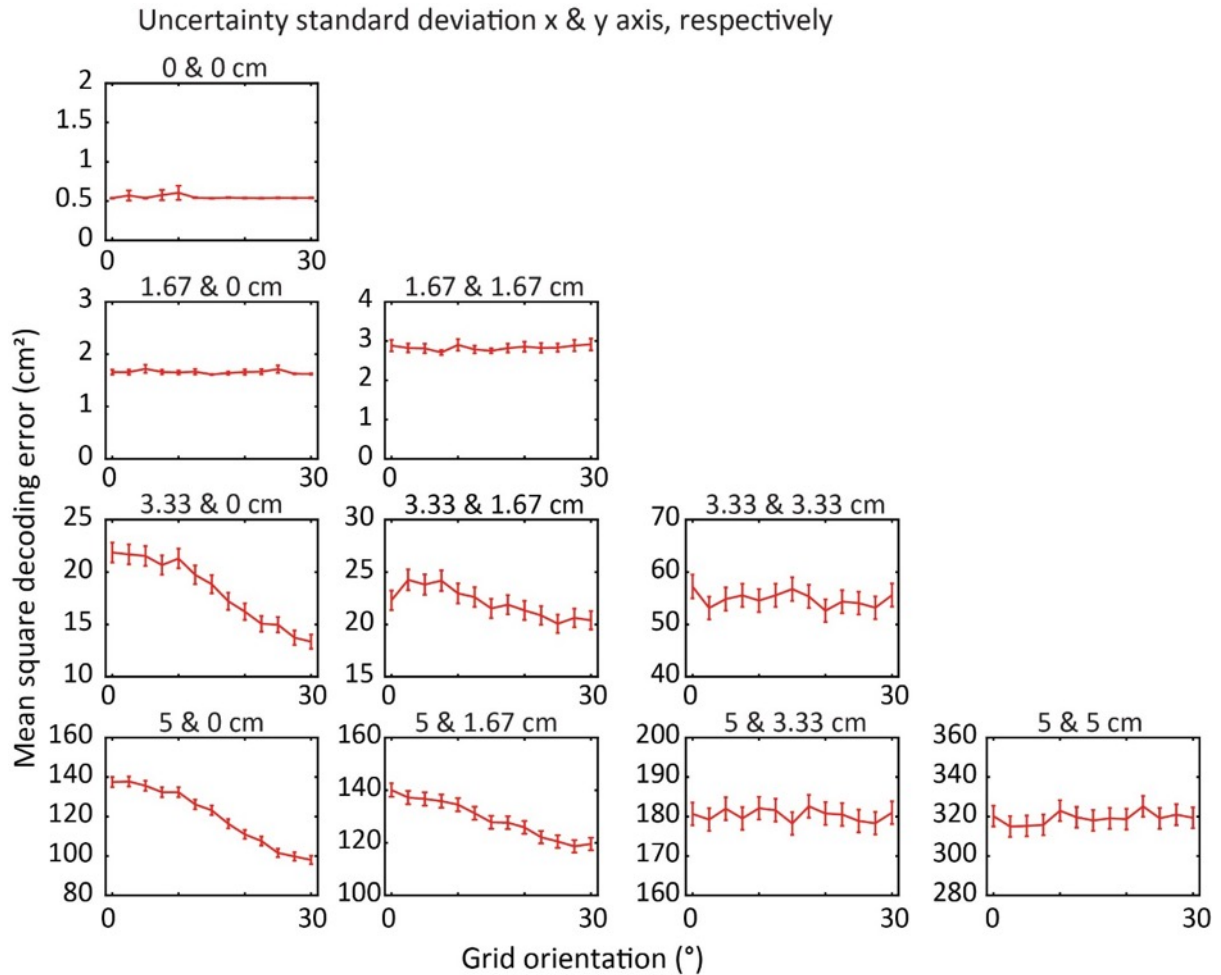
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935 **SUPPLEMENTAL INFORMATION**

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937 **Supplemental Figures :**

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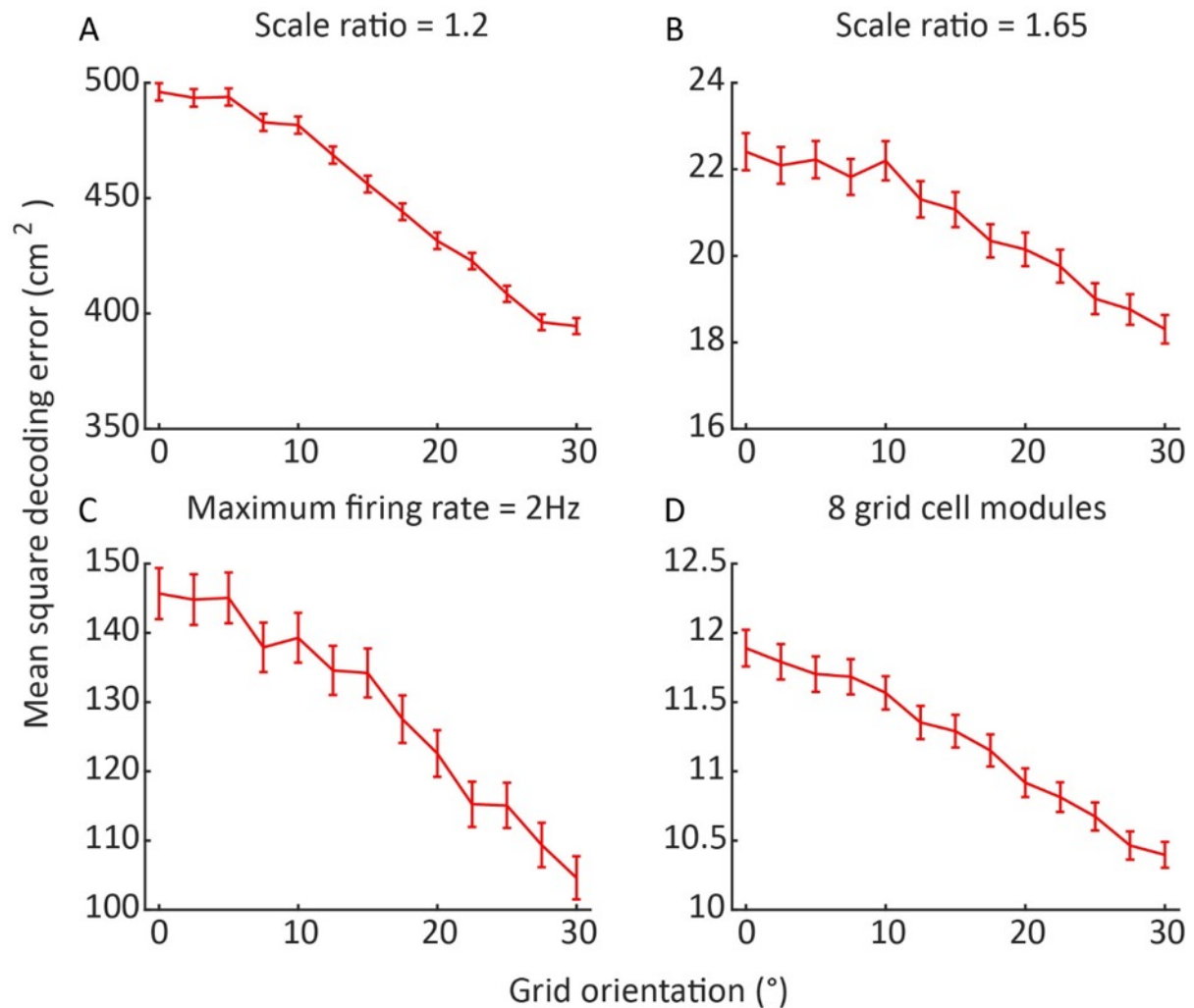


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940 **Figure 1 – figure supplement 1. More extreme anisotropy in spatial uncertainty results**
941 **in a more pronounced dependency of self-localisation accuracy on grid orientation.**

942 The performance of grid cell systems was assessed while independently varying the
943 degrees of spatial uncertainty in two orthogonal axes. When uncertainty is equal in both
944 axes performance does not depend on the orientation of the grid pattern. As uncertainty
945 becomes more anisotropic, self-localisation is more accurate in grid cell systems in which
946 the grid pattern axes are aligned away from the axis of greatest spatial uncertainty.

947



948

949 **Figure 1 – figure supplement 2. The dependency of self-localisation accuracy on grid**
950 **orientation is stable within reasonable sets of grid cell system parameters.**

951 Performance is consistently best when the grid axes are aligned away from the axis of least
952 spatial uncertainty, across variations in the parameters of the grid cell system. Error bars

953 indicate 95% confidence interval, $n = 150,000$. **A** Grid period scaling factor reduced to 1.2. **B**

954 Grid period scaling factor increased to 1.65. **C** Grid cell maximum firing rate reduced to 2Hz.

955 (In order to compensate for increased effects of noise in this system, the number of cells per
956 module was quadrupled. Due to the high computational intensity of this simulation $n =$

957 75,000.) **D** Four further grid cell modules added, with scales continuing to increase

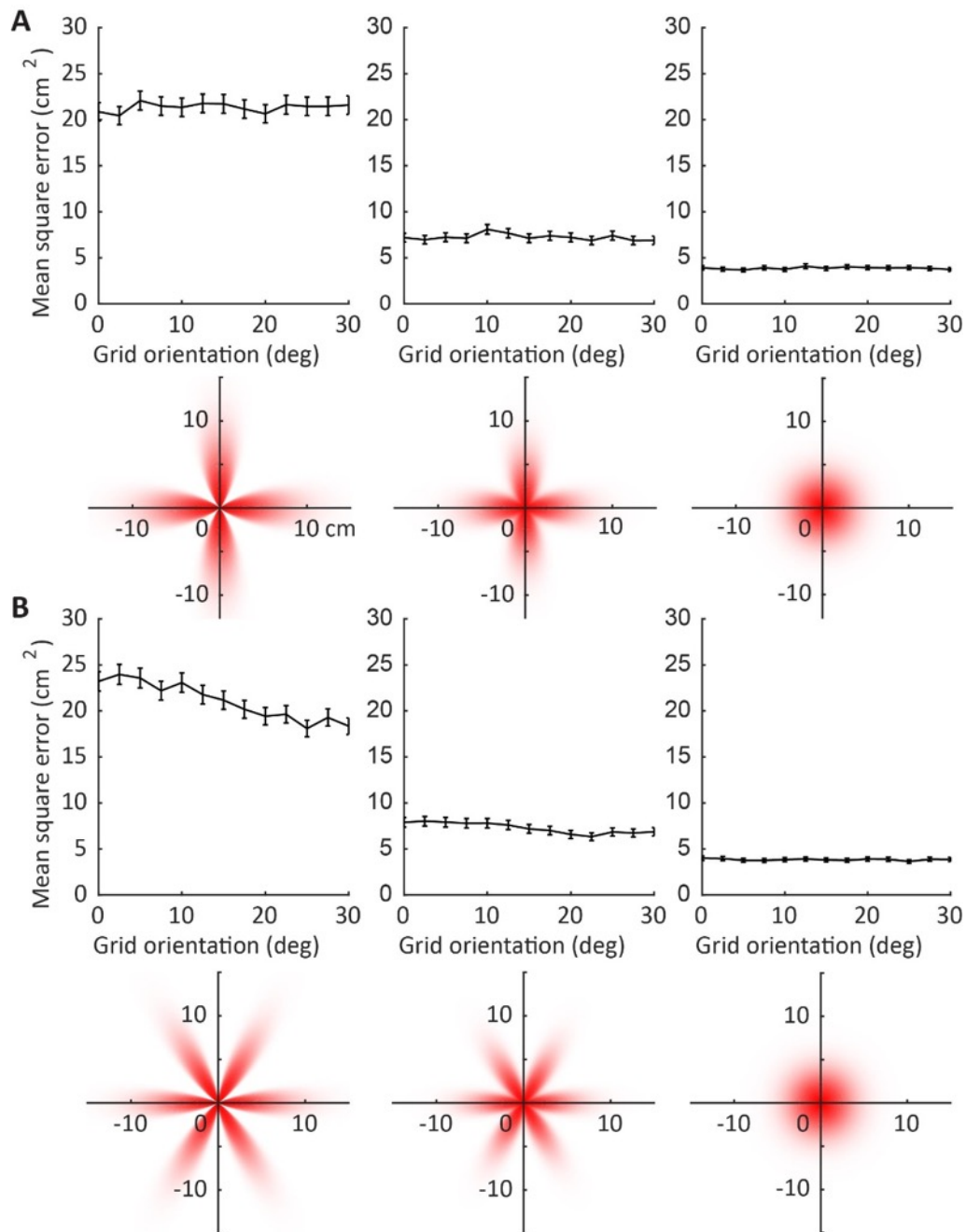
958 geometrically.

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Figure 1 – figure supplement 3. Higher-order uncertainty distributions and self-

965 **localisation accuracy. A** Four-leaf uncertainty distribution. Across different grid orientations

966 the different grid axes are variously aligned and misaligned with the directions of greatest

967 and least certainty. No clear trend for an optimal grid orientation is apparent. **B** Six-leaf

968 distribution. Across different grid orientations the grid axes are either aligned or misaligned

969 with the high-uncertainty directions, producing the same trend as the simple (two-leaf)

970 anisotropic uncertainty distribution. Localisation performance is best when the grid axes are

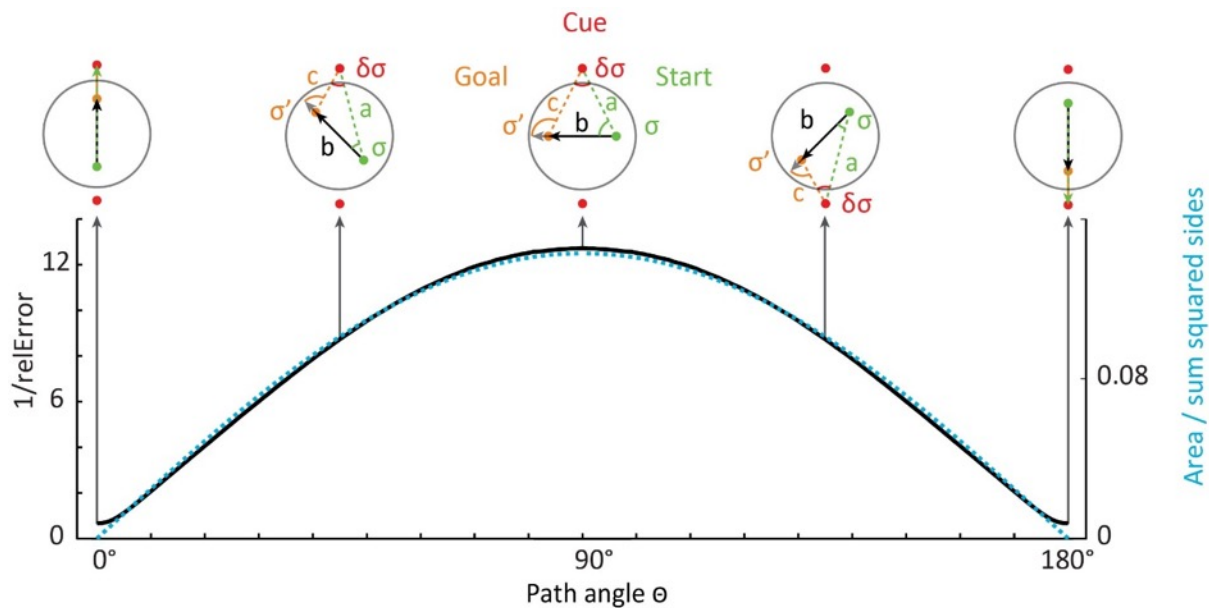
971 aligned away from the axis of least spatial uncertainty. Error bars indicate 95% confidence

972 interval, $n = 150,000$.

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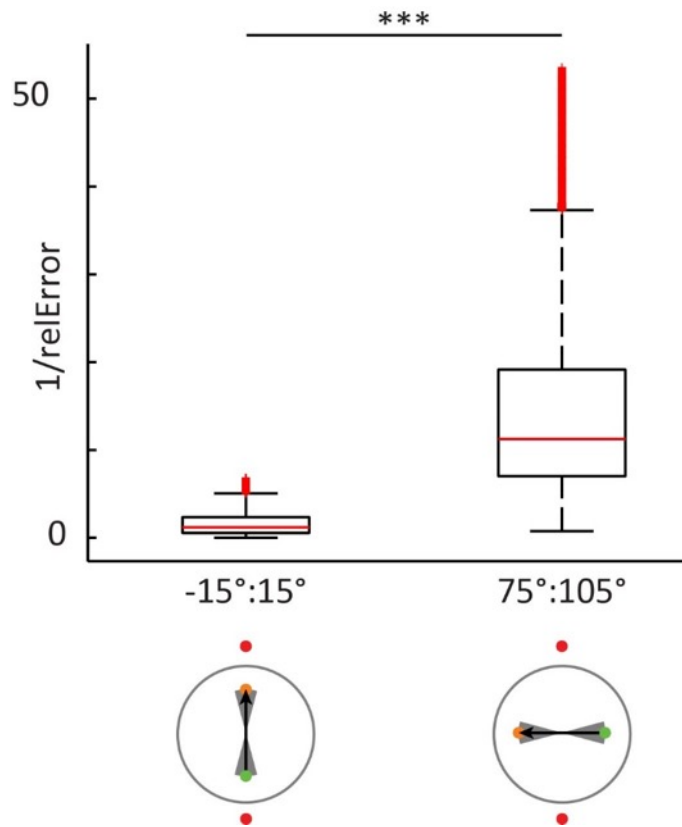
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Figure 1 – figure supplement 4. Triangulation under noise in circular and square

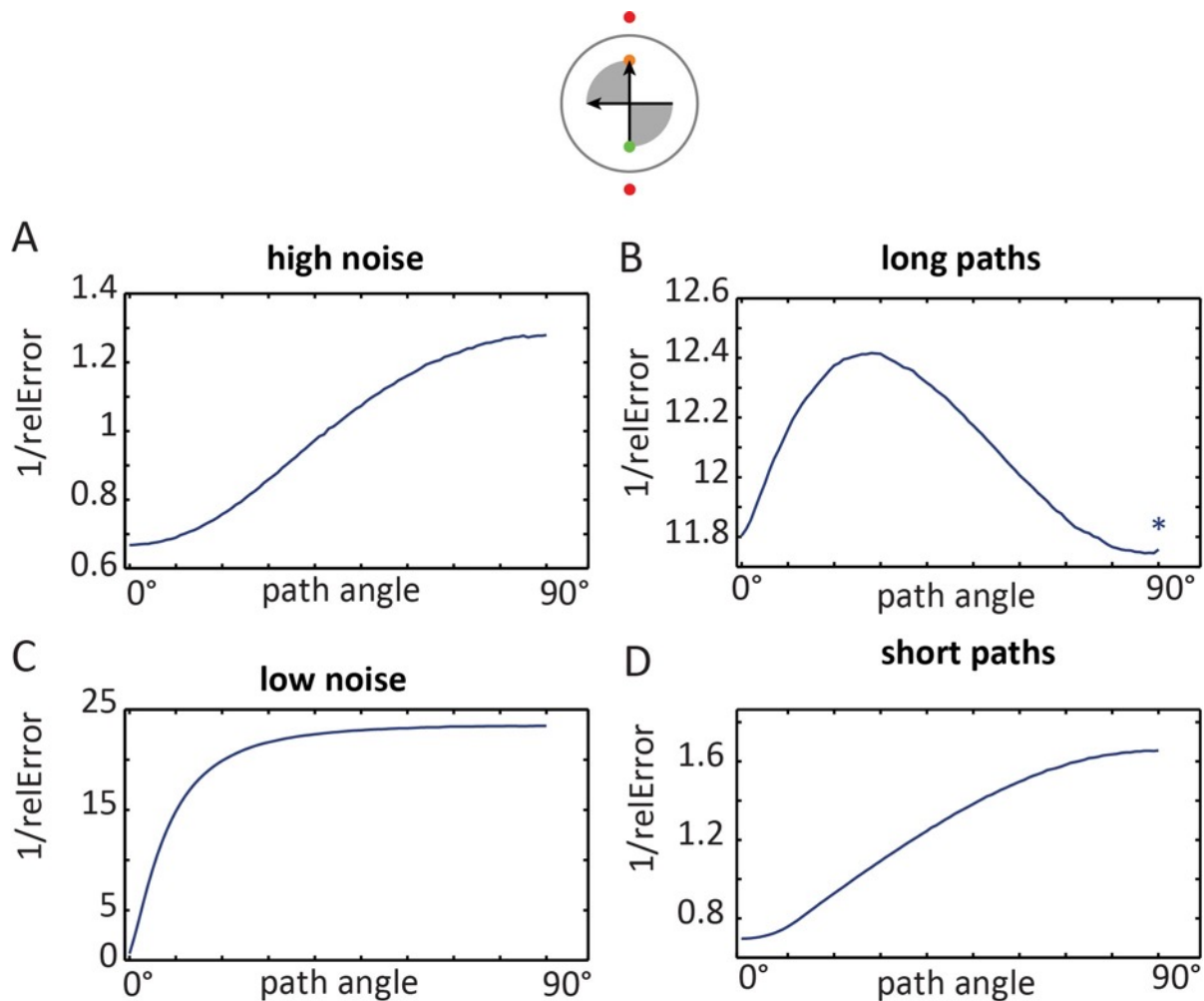
environments. To test the impact of anisotropic optic flow information on spatial computations, we performed a biologically inspired simulation of Euclidean triangulation. For example, an estimate of the distance between start and end points was computed from noisy estimates of the angles and distance to one of the cues using equation 2. All sides (a-c) of a triangle served as both inputs and distance to be estimated, before the results were averaged on one iteration. The median noise resilience ($1/\text{relative error}$ [relError]) across iterations is plotted in black. On a given iteration, relErr is determined as the absolute distance error / side length, averaged across the three sides of each triangle. Black arrows indicate example paths between two observer positions (start in green and goal in orange, always crossing the centre; see Materials and Methods for details). Red dots show polarising cues. Most accurate triangulation was achieved on paths orthogonal to the polarisation axis (10^3 repetitions for each triangle, $90^\circ \pm 15^\circ$ versus $0^\circ \pm 15^\circ$, two-sided Wilcoxon signed-rank test: $Z=1026.42$, $p<0.001$). Optimal path angle was well predicted by a quality measure for triangulation (triangle area / sum of squares of the side lengths; $R=0.99$, $p<0.001$). This measure increases for more equilateral triangles.



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996

997 **Figure 1 – figure supplement 5. Magnitude of noise resilience of directional bin of**
998 **paths centred on peaks and troughs of Figure S1.** The most accurate triangulation was
999 achieved on paths orthogonal to the polarisation axis. $10 \cdot 10^3$ repetitions for each triangle,
1000 $90^\circ \pm 15^\circ$ versus $0^\circ \pm 15^\circ$, two-sided Wilcoxon signed-rank test: $Z=1026.42$, $p<0.001$. The
1001 grey shaded area in the bottom panels indicate the range of paths that were tested. The box
1002 edges denote the 25th and 75th percentiles and central red mark the median. The whiskers
1003 extend maximally to $q_3 + 1.5 \cdot (q_3 - q_1)$ and minimally to $q_1 - 1.5 \cdot (q_3 - q_1)$, where q_1 and q_3
1004 are the 25th and 75th percentiles, respectively. A red + denotes points outside this range,
1005 with the exception of the upper 10% of values that were omitted for display purposes.
1006 Statistical testing included all data.

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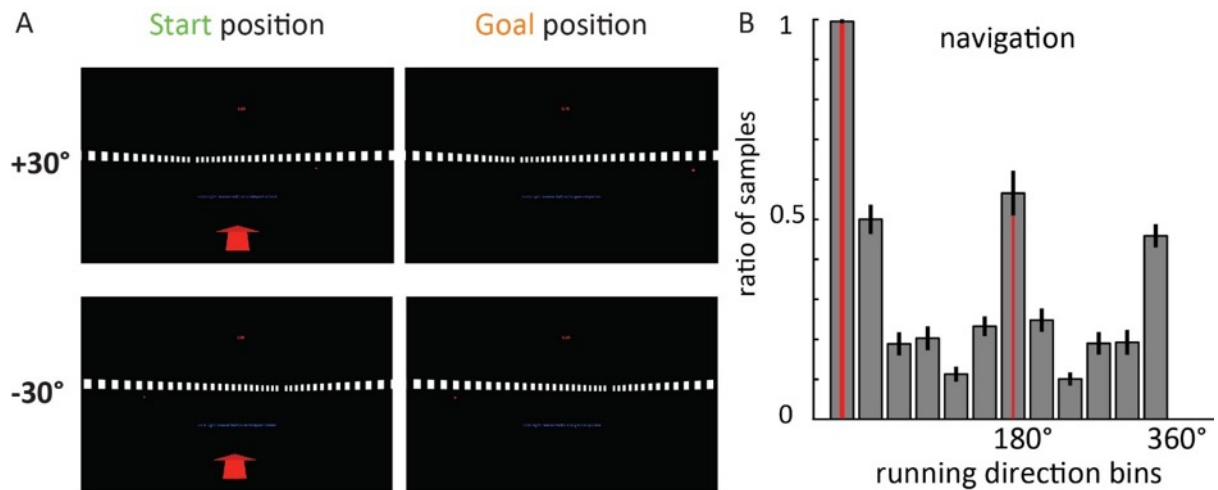
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Figure 1 – figure supplement 6. Effects of noise levels and path length on optimal triangulation paths Environment with a single axis are defined by two cues (analogous to the two fMRI experiments and the behavioural experiment). All (A, C, D) except the long path condition (B) yielded an optimum at 90°. However, this extreme case never occurred for participant's paths in the fMRI experiments due to the limitations of the circular boundary. The average length of straight (+-45°) paths was 11% of the polarisation axis' length in fMRI experiment 1 (12% in fMRI experiment 2) – See Figure 3 – figure supplement 1E-F. High noise = randomly sampled from a distribution with a 10 times larger sigma (62.6, instead of 6.26, see Materials and Methods). Low noise = randomly sampled from a distribution with a 10 times smaller sigma (0.626, instead of 6.26). Long paths = simulated path length was equal to the length of the polarisation axis (instead of 50%, see Materials and Methods). Short paths = simulated path length was 5% of the length of the polarisation axis (instead of 50%, see Materials and Methods). Asterisk = plots have been smoothed with a 5°-wide kernel for display purposes. The grey shaded area in the top panels indicates the range of paths that were used.



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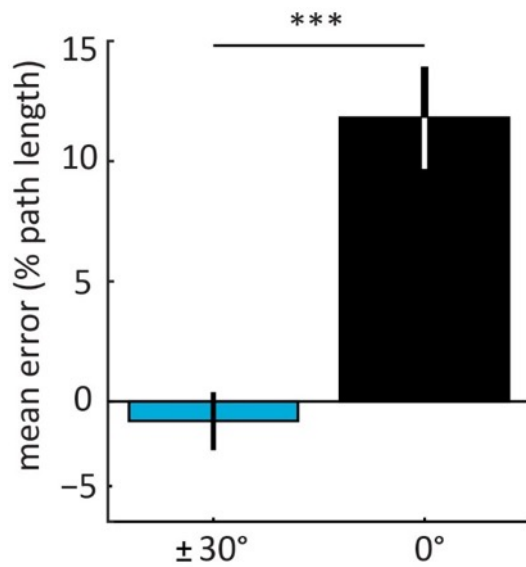
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Figure 2 – figure supplement 1. A Additional views of the behavioural experiment at the beginning (Start) and end (Goal) of a path. Note that the background was rendered at infinity (see Materials and Methods), such that it did not change during teleportation in the $\pm 30^\circ$ or the 0° condition (Figure 2BC). **B** Sampling of movement direction. Participants were not only exposed to translations in the $\pm 30^\circ$ and 0° condition, which might force spatial representations to align with those directions. During free navigation to a start position, all other directions were sampled, albeit not homogeneously (Friedman test: $\chi^2_{(11)} = 179$, $p < 0.0001$; note that on some trials the start position was on the opposite side of the environment).

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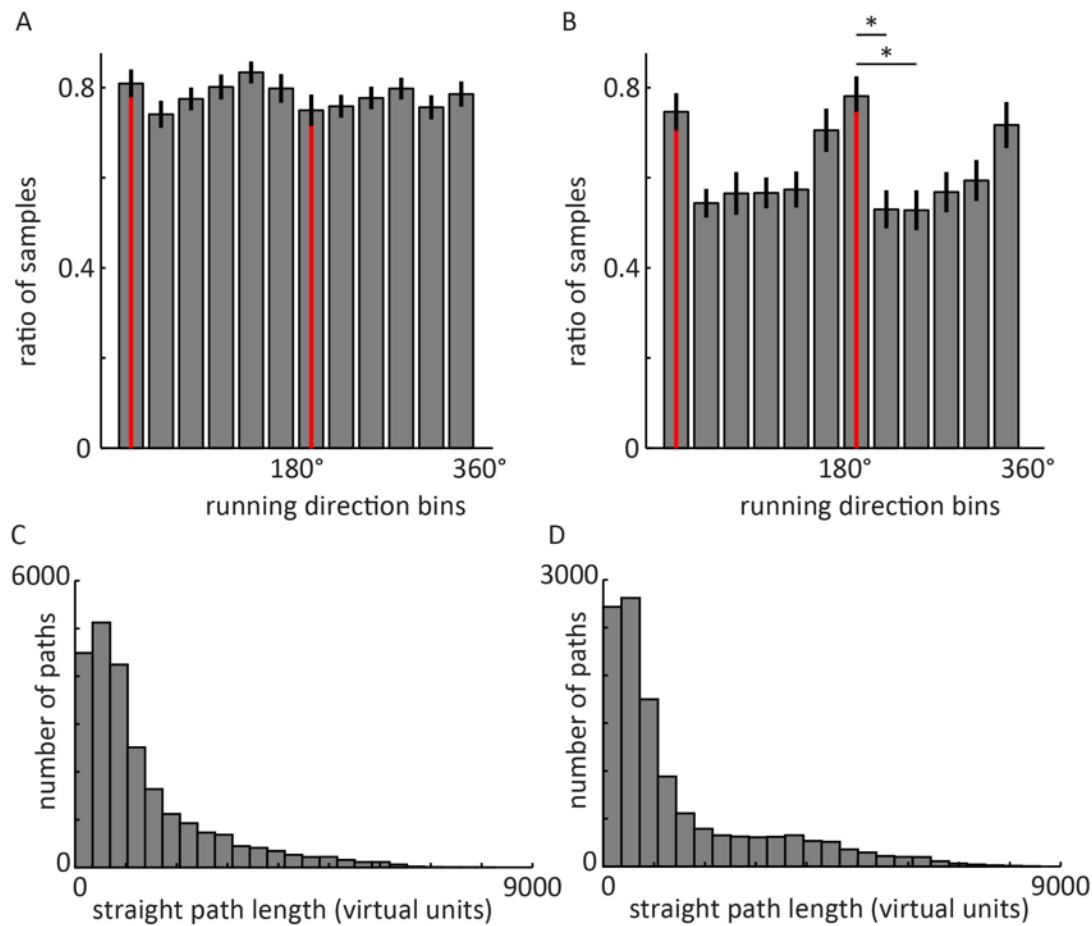
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1041 **Figure 2 – figure supplement 2. Mean distance estimation error (in percent of correct**
1042 **path length) in the behavioural experiment** (Figure 2). Paths along the polarisation axis
1043 (0°) yielded less accurate distance estimation than oblique paths ($\pm 30^\circ$). Paired, two-sided t-
1044 test $N=20$; $T_{(19)} = 5.47$, $p < 0.001$. See Figure 2C for an effect in the same direction for
1045 absolute errors. Bars show errors in percent of correct path length averaged across
1046 participants \pm S. E. M.; Mean 0° condition = 11.8 %; Mean $\pm 30^\circ$ condition = -0.8 %.

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1051 **Figure 3 – figure supplement 1. Behavioural analyses of fMRI experiment 1 (A, C, E)**

1052 **and fMRI Experiment 2 (B, D, F).** Spatial memory performance: the decreases in drop error

1053 indicate that participants in both experiments were able to successfully navigate and

1054 remember locations in the sparse virtual environments. Participants learned the locations of

1055 6 objects in fMRI experiment 1 (A) and 4 objects in fMRI experiment 2 (B; See Materials and

1056 Methods). Red line denotes mean drop error (i.e. Euclidean distance in virtual units between

1057 participants' response location and the correct location of a given object on a given trial)

1058 across participants. Grey outline denotes standard error of the mean. For display purposes,

1059 results are shown up to trial number 90 for consistency. Variations in the number of trials

1060 across participants were due to differences in self-paced completion of trials. **C-D** Sampling

1061 of running directions. The number of samples of movements in 30° bins of running direction

1062 was normalised within participants for comparability across participants by dividing it by the

1063 maximum number of samples in any of the 12 bins, thereby yielding a maximum value of 1

1064 for a bin. **C** FMRI experiment 1 (polarisation axis defined by configural cues), N = 26: A non-

1065 parametric Friedman test of median differences among repeated measures of directional

1066 sampling was revealed no clear differences ($\chi^2_{(11)}=9.5, p=0.57$). **D** FMRI experiment 2

1067 (polarisation axis defined by non-configural cues), N = 24: A non-parametric Friedman test of

1068 median differences among repeated measures revealed differences ($\chi^2_{(11)} = 36.7$, $p < 0.001$).
1069 Post-Hoc tests with Tukey-Kramer correction for multiple comparisons revealed that
1070 particularly runs along the environmental axis at 165° ($\pm 15^\circ$) occurred more often than runs
1071 oblique at 195° ($\pm 15^\circ$) and 125° ($\pm 15^\circ$). Asterix: $p < 0.05$ Note that both the absence of a
1072 difference in fMRI experiment 1, as well as more frequent runs along the polarisation axis in
1073 fMRI experiment 2 speak against the possibility that the environmental effects on
1074 hexadirectional activity reported above would be due to biases in navigation behaviour. Error
1075 bars show S.E.M. over participants. **E-F** Distances of running paths. Histograms show the
1076 number of straight paths for different distances. Path length was determined as the
1077 Euclidean distance between start and end point of a path with continuous movement and
1078 rotations of less than $\pm 45^\circ$ (i.e. a 90° -wide bin). FMRI experiment 1 (E): mean = 1316.2 vu.
1079 FMRI experiment 2 (F): mean = 1493.5 vu.

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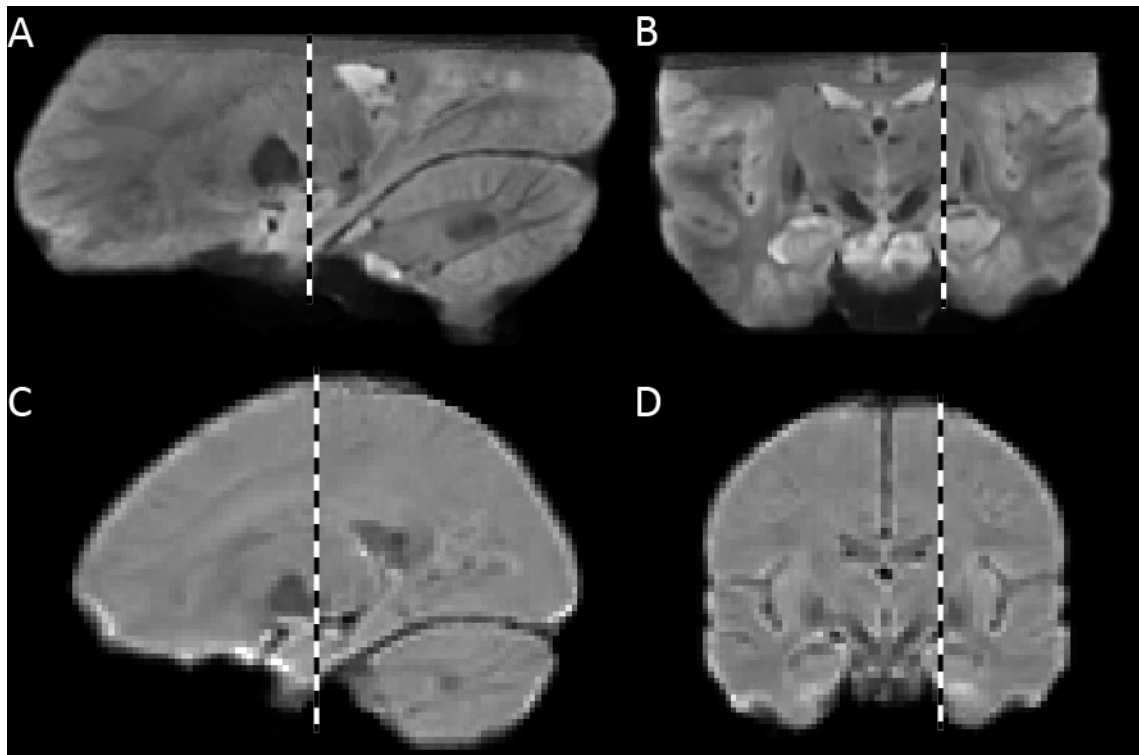
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Figure 5 – figure supplement 1. Mean functional images across participants used as template brains. A-B Template for fMRI experiment 1 (7T scanner). **C-D** Template for fMRI experiment 2 (3T scanner). Dashed lines indicate the location of the slice in the corresponding orientation in the panel above or below. Template images were created with Advanced Neuroimaging Toolbox (ANTS; <http://www.picsl.upenn.edu/ANTS/>) based on individual, mean 3D echo-planar images. Note the relatively high contrast for functional images in the 7T data, with clear grey and white matter intensity differences even in the medial temporal lobes.

1104 **Competing interest:**

1105 The authors declare no competing interests.

1106

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