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Authors
Popescu, Sergiu Tcaci
Wexler, Mark

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Spontaneous body movements in spatial cognition

Sergiu TCACI POPESCU (sergiusergiu@gmail.com) and Mark WEXLER (mark.wexler@gmail.com)
CNRS & Université Paris Descartes
Laboratoire Psychologie de la Perception
45, rue des Saints-Pères
75006, Paris, France

Abstract

People often perform spontaneous body movements during spatial tasks. How are these spontaneous gestures related to spatial problem-solving? We measured spontaneous movements during a perspective-taking task inspired by map reading. Analyzing the motion data to isolate its rotation and translation components in specific geometric relation to the task, we found out that most participants executed spontaneous miniature rotations of the head that were significantly related to the main task parameter. These head rotations were as if participants were trying to align themselves with the orientation on the map, but with tiny amplitudes, typically below 1% of the actual movements. Our results are consistent with a model of sensorimotor prediction driving spatial reasoning. The efference copy of planned movements triggers this prediction mechanism. The movements themselves may then be mostly inhibited; the spontaneous gestures that we measure are the visible traces of these planned but inhibited actions.

Keywords: spatial cognition; motor action; sensorimotor prediction; embodied cognition; mental simulation

Introduction

Motor activity in spatial tasks

People often perform spontaneous body movements during spatial tasks such as giving complex directions or orienting themselves on maps. Spontaneous gestures in spatial tasks have been studied by Chu & Kita (2011), who showed that their participants spontaneously produced hand gestures while performing a mental rotation task. Motor activity can also trigger mechanisms that simulate the outcome of an action (see Wolpert & Flanagan, 2001, for a review of sensorimotor prediction) and thus infer otherwise unavailable information. For instance, Wexler, Kosslyn, & Berthoz (1998) and Wohlschläger & Wohlschläger (1998) showed that unseen manual rotations improved performance in mental rotation tasks when the mental and manual rotations were in the same direction, and interfered with mental rotation when the two were in opposite directions. The execution of at least some of the visuo-spatial tasks mentioned above includes a motor component that can either improve task performance or interfere with it. This conclusion is supported by the findings of neuroimaging studies (Kosslyn, Ganis, & Thompson, 2001).

Spatial perspective-taking (SPT)

Spatial perspective-taking occurs when one adopts a viewpoint different from one's physical viewpoint. SPT is more difficult when the imagined perspective differs from the actual (physical) one by a rotation than by a translation (Rieser, 1989). Performance after an imagined rotation depends on the absolute magnitude of the rotation angle between the actual and the imagined perspective and shows the typical and robust angular disparity effect: the bigger the angle of rotation to the imagined perspective, the lower the performance. More importantly, when people are allowed to move to the location of their imagined or novel perspective, even in absence of visual and auditory cues, performance after perspective rotations is greatly facilitated and may even attain the baseline level.

Spatial updating seems simple and automatic if a person were to perform the full rotations that he or she imagines. The updating is therefore driven by a sensorimotor prediction mechanism, and this mechanism is activated by motor plans or efference copies of the motor command (Wolpert & Flanagan, 2001). The planned action itself could be wholly or partly inhibited further downstream in the motor system. If spontaneous movements are a visible reflection of such simulated but inhibited actions, they should be correlated in some geometrically specific way with the mental task being performed. To determine if this is so was the major goal of our study.

Methods

24 unpaid participants took part in the experiment. The motion tracking data of 5 participants did not attain our inclusion criterion (see below) and were discarded. We therefore performed all analyses on the data of the remaining 19 participants (8 women, mean age 33.8, standard deviation (SD) 7.1 years).

The participants were told to watch on a computer display a simple map depicting the crossing of two streets. (see Fig. 1). The participants' task was to answer as quickly and accurately as possible if, at the intersection, they needed to turn left or right in order to reach the (red) dot.

The stimuli were parametrized by two variables: the *deviation angle* (see Fig. 1), and the *corner angle* (not shown in Fig. 1). We take the upward orientation as our "zero" because pilot results showed that it is easiest to perform the task when one's initial imagined orientation is upwards. Deviation angles are taken as positive counterclockwise and negative clockwise. The second independent variable, the corner angle, is the angle between the two streets on the map. It was used to mask the similarity between the trials with the same value of the deviation angle.

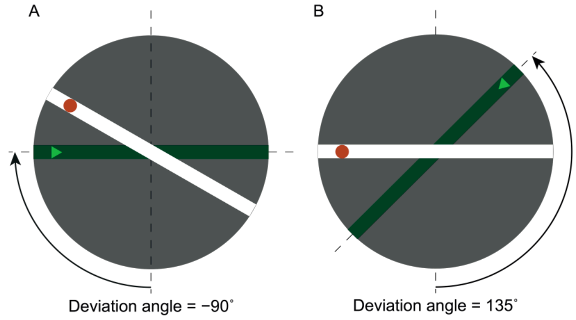

Figure 1: Two examples of stimuli (the dashed lines, the angle arrow and text were not part of the stimuli). Every stimulus represents the crossing of two streets. Participants imagined being on the darker (green) street, at the position of the triangle, and facing the intersection. We call this orientation the *imagined orientation*. The task was to decide if at the intersection one should turn left or right in order to reach the (red) dot on the other street. We call the angle between the 6 o'clock (or upwards-facing) direction and the imagined orientation the *deviation angle*. (A) An example stimulus with deviation angle of −90 deg. (B) An example stimulus with deviation angle of +135 deg.

Participants were seated at about 60 cm from a computer display on which the stimulus was displayed. They used the left and right shift keys on a keyboard to answer respectively "left" and "right" with the corresponding hand. Each trial began with the display of a central fixation red cross. After 0.5 seconds, the stimulus was displayed until participant's answer. We recorded both the response and the response time (RT). The experimental session lasted for about 40 minutes and included 10 practice trials and 500 experimental trials. Every one hundred trials were followed by a pause; its duration did not exceed 5 minutes.

Participants' head and shoulder movements were recorded using a CODA cx1 scan unit of a Codamotion optical motion tracking system (Charnwood Dynamics Ltd., UK); we used three sensors for each body part. The system recorded the spatial coordinates of each of the six sensors at a sampling rate of 200 Hz.

We used a within-participant factorial design. The main independent variable, the deviation angle, had 8 levels (0˚, ±45˚, ±90˚, ±135˚, 180˚). The second independent variable, the corner angle, had 10 levels (±30˚, ±60˚, ±90˚, ±120˚, ±150˚). Five repetitions were set for each condition except for deviation angle angles of 0˚ and 180˚, for which 10 repetitions were set. Trials were presented in random order.

A trial was considered valid if all sensor values were available for at least half of its duration and only subjects with at least 50% of valid trials were included in the motion analysis. Only data from correctly answered valid trials with a RT that did not exceed the mean RT plus 3 SD were included in the analyses. A rectangular moving average filter of 20 samples (0.1 s) was applied in order to smooth the motion data. The trials with a deviation angle of 180 deg were excluded from the analysis of the geometrical properties of rotations and translations as the sign of the angle cannot be used to discriminate the direction of rotations or translations.

We used the distance travelled by a body part (by summing the absolute Euclidean distances between all successive samples of a sensor) as a first measure of motion. If participants did not move more for higher values of deviation angles, our hypothesis would be invalidated from the start. We selected the maximum path length among the three sensors for each body part as the representative value of its motion extent. Since the path length is always positive, we posited a simple regression model of the path length on the absolute values of deviation angle: $\mathbf{P}_i = \mathbf{a} + |\theta_i|\,\mathbf{b}$, where $\mathbf{P}_i$ is the maximum path length of the three motion sensors on trial *i* (expressed in mm), θ_i the deviation angle on that trial, **b** a regression coefficient, and **a** a constant term. If the slope is found to be positive, we can proceed to a more specific analysis, which consists in decomposing the motion in its translational and rotational components and analyzing their geometrical specificity in relation to the signed values of deviation angles.

For the sake of the detailed motion analysis, we assume that both the head and shoulders undergo rigid motion in space—a combination of rotation and translation. We extracted the rotation and translation, using an optimization algorithm. We first calculated the relative vectors between the three sensors, which isolates the rotation component of the rigid motion. Our algorithm then searched through the (three-dimensional) space of rotations, finding the rotation that most closely matched the final relative vectors. We calculated the translation separately by performing vector subtraction between centers of mass of the three sensors for the head and shoulders.

For each sample of sensor positions provided by the motion tracker, we computed participants' head and shoulder rotations (axes and angles) and translations with respect to their initial orientation and position, respectively. We then selected the maximum values of rotation and translation reached during the trial. We could not predict the axis about which the spontaneous rotations take place. We therefore posited the following simple linear regression model, in terms of axis-angle rotation vectors (indicated in boldface) for the relation between spontaneous movements and task variables: $\mathbf{R}_i = \theta_i\,\mathbf{r}$, where $\mathbf{R}_i$ is the maximum rotation—of either the head or the shoulders—on trial *i* (expressed in the axis-angle vector representation), θ_i the deviation angle on that trial, and **r** a triplet of regression coefficients. Thus, the vector **r** represents the rotation (again, as a vector in axis-angle space) that the participant would perform for deviation angle θ equal to 1 deg. We decomposed this vector into its axis-angle components: $\mathbf{r} = z\,\hat{\mathbf{a}}$, where its length or norm, *z*, is a regression coefficient that we will call the *spontaneous rotation coefficient*, and its direction, $\hat{\mathbf{a}}$, the unit vector that corresponds to the axis of rotation. Our regression therefore yields both the spontaneous rotation coefficient and the axis of spontaneous rotation.

We posited a similar model for translations: $\mathbf{T}_i = \theta_i\, w\, \hat{\mathbf{u}}$, where $\mathbf{T}_i$ is the maximum translation vector of the head or shoulders, and $\hat{\mathbf{u}}$ is a unit vector indicating the direction of translation, and w the spontaneous translation coefficient.

To calculate statistical confidence intervals of these spontaneous motion coefficients, we performed a bootstrap. For each bootstrap resample j, we calculated the rotation vector $\mathbf{r}^{(j)}$ [or the translation $w^{(j)}\ \mathbf{t}^{(j)}$]. We then calculated a 95% confidence ellipsoid for these points. If the origin fell outside this ellipsoid, then the regression was said to yield a coefficient statistically different from zero. We used the geometric mean of the ellipsoid semi-axes as a measure of standard error of the spontaneous motion coefficients.

Results

Response times and error rates

Overall, the mean RT on raw unfiltered data was 1.17 ± 0.38 s (± between-subject SD). Increasing the deviation angle lowers performance, increasing the RT, as shown in Fig. 2.

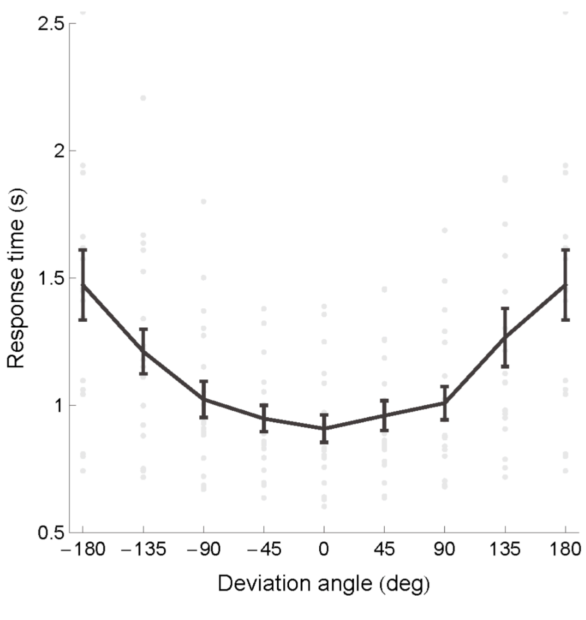

Figure 2: RT as a function of the deviation angle. Gray dots represent individual participants' data, the black curve the mean, and error bars between-subject standard errors. The data for deviation angles ±180° is shown twice. Several outlying datapoints are not shown.

The mean reaction time was submitted to a repeated-measures ANOVA with the factors: sign of deviation angle (2 levels), absolute value of deviation angle (6 levels, excluding 0 and 180 deg), sign of corner angle (2 levels) and absolute value of corner angle (5 levels). The analysis revealed a significant main effect of absolute value of the deviation angle ($F_{2,36} = 29.1$, $p < 0.001$, Huynh-Feldt corrected), a significant main effect of the sign of corner angle ($F_{1,18} = 16.9$, $p < 0.001$), a significant main effect of the absolute value of corner angle ($F_{3.4,60.6} = 8.3$, $p < 0.001$) and a significant third-order interaction between the sign of deviation angle, the sign of the corner angle and the absolute value of corner angle ($F_{2.8,50.9} = 4.3$, $p < 0.01$). The main effect of the sign of the deviation angle was not statistically significant nor were the other interactions.

To quantify the relation between the deviation angle and the RT, we calculated the slopes of the linear regression of the RT on the absolute values of the deviation angle for every participant. (Since the sign of the deviation angle had no effect on the response times, we collapsed data for positive and negative deviation angles.) All individual slopes were positive and statistically significant (bootstrap with 10^4 resamples, $p < 0.05$); the mean slope was 3.09 ± 2.30 ms/deg (± between-subject SD). In other words, mean RT increased by 3.09 ms for every additional degree of deviation angle. The plot of RT versus deviation angle (Fig. 2) has a noticeably curvilinear shape, with the RT slope seemingly higher for deviation angles above 90 deg. The mean slope for deviation angles between 0 and 90 deg was 1.20 ± 0.89 ms/deg, whereas between 90 and 180 degrees it was 5.05 ± 3.82 ms/deg. This difference between slopes for small and large deviation angles was statistically significant (paired $t_{18} = 5.41$, $p < 0.0001$) and showed that RTs increased faster (more than 4 times faster, according to the means) as a function of deviation angle above 90 deg.

The median error rate was 1.2 ± 0.6% (± between-subject median absolute deviations). Overall, the error rate was very low: the task was seemingly well understood by our participants and easy to perform. The analyses of the relation between error rates and deviation angles lead to similar findings as the ones of the RT and are not provided here.

Spontaneous body movements and their relation to the task

Analysis of Path Length As a first analysis of the relation between task performance and body movements, we wanted to see if there was a relationship between the extent of spontaneous motion and the deviation angle. As a measure of motion extent, we used the length of the path traveled in space. Fig. 3 shows the mean path lengths as a function of the absolute deviation angle.

The mean path length across participants and deviation angles is 13.1 ± 10.2 mm (± between-subject SD) for the head and 10.3 ± 6.9 mm for the shoulders. The slope of the linear regression (including a constant term, see Methods) of path lengths on the absolute deviation angles provides an indication on the relation between the movements and the deviation angle: if positive, it would indicate that the participants move more in trials with higher deviation angles. For head movements, 17/19 (89%) regression slopes were positive and 13/19 (68%) were significantly so (bootstrap with 10^4 resamples, $p < 0.05$); the mean slope was 0.038 ± 0.058 mm/deg (± between-subject SD). For the shoulders, 17/19 (89%) regression slopes were positive and 12/19 (63%) were significantly so (bootstrap with 10^4 resamples, $p < 0.05$); the mean slope was 0.026 ± 0.041 mm/deg.

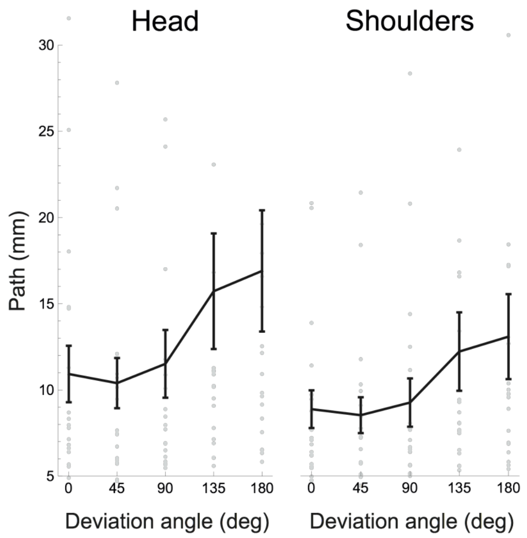

Figure 3: Mean path length traveled by the head and shoulders as a function of deviation angle. Gray dots represent individual participants' data, the black curve the mean, and error bars between-subject standard errors. Several outlying datapoints are not shown.

This analysis of path lengths shows that for most participants there was a relationship between the *absolute extent* of spontaneous movements and the absolute value of the principal task parameter, the deviation angle. Because the movements of the head and shoulders were nearly rigid, for further analysis we decomposed them into the two components of rigid motion, rotations and translations.

Analysis of Absolute Amplitude of Rotations As stated in the Methods, for each trial we calculated the maximal rotation of the head and shoulders with respect to their initial orientations at the start of the trial. We represented these rotations as 3D vectors using the axis-angle representation, in which the length of the vector is the angle of rotation and its direction the axis.

To begin with, we analyzed only the angles of the maximal rotations. As in the preceding analysis, we wished to test whether this measure of absolute magnitude of rotation was correlated with task difficulty, i.e., the absolute value of deviation angle. Fig. 4 shows the mean maximal rotation magnitude as a function of the absolute deviation angle.

The overall mean rotation amplitude is 1.57 ± 0.5 deg (± between-subject SD) for the head and 0.78 ± 0.17 deg for the shoulders. Some of the spontaneous rotations were not specifically related to the main task parameter, as shown by the presence of rotations even when deviation angle is zero.

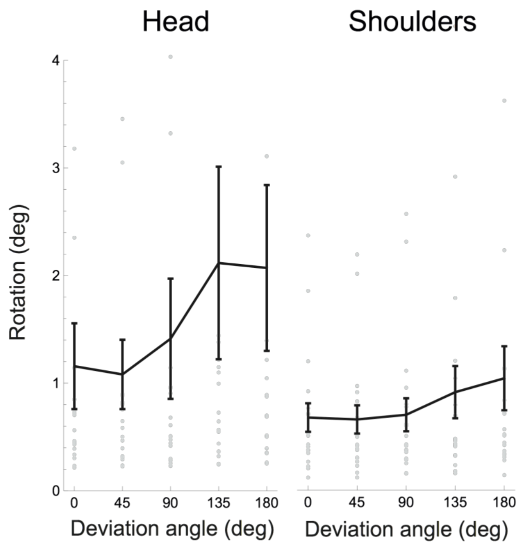

Figure 4: Absolute rotation amplitude, for the head and shoulders, as a function of the absolute deviation angle. Gray dots represent individual participants' data, the black curve the mean, and error bars between-subject standard errors. Several outlying datapoints are not shown.

We performed a linear regression (including a constant term) of the rotation amplitude versus absolute deviation angles to quantify the relation between the rotations and the deviation angles. We found out that 17/19 (89%) regression slopes were positive for both head and shoulder rotations and 10/19 (53%) for the head and 7/19 (37%) for the shoulders were significantly so (bootstrap with 10^4 resamples, $p < 0.05$); the mean slope was 0.006 ± 0.013 (± between-subject standard deviations) for the head and 0.002 ± 0.005 for the shoulders.

The analysis of absolute rotation angles shows that there was a relationship between the *absolute amplitudes* of spontaneous rotations and the deviation angle. It doesn't tell us, however, if this relationship was geometrically specific. Did participants spontaneously move in one direction for the positive deviation angles and in the opposite direction for the negative ones?

Directional Analysis of Rotations To answer the question above, we performed a linear regression of the full axis-angle rotation vectors (i.e., including the direction of rotations in addition to their amplitudes) on the deviation angle—rather than just its absolute value—of the corresponding trial. We call the slopes of these linear regressions the spontaneous rotation coefficients (see Methods for details).

For head rotations, the mean spontaneous rotation coefficient is 0.007 ± 0.018 (± between-subject SD); the median coefficient is 0.001 ± 0.0009 (± between-subject median absolute deviations). For the shoulders, the mean coefficient is 0.001 ± 0.002; the median coefficient is 0.0005 ± 0.0002. The interpretation of these parameters, for example for head spontaneous rotations, is as follows: on the average, participants rotated their head by 0.7% (or 0.1%, if we use the medians) of the deviation angle. Contrary to the preceding analyses, we have extracted the directionally-specific component of the spontaneous rotations: rotations that are in opposite directions for clockwise and counterclockwise deviation angles. The axis of these rotations varies from one participant to the next; we will return to the question of axes below.

To test whether these correlations were statistically significant, we stepped back to our original regression model, $\mathbf{R}_i = \theta_i \mathbf{r}$ (recall that the spontaneous rotation coefficients are the lengths of the regression vectors **r**), and used the regression vectors **r** for significance analysis. We performed a bootstrap resampling (10^5 resamples) of the vectors **r** and calculated the 95% confidence ellipsoid of these vectors (see Methods).

First of all, an omnibus regression analysis, including all data sets of all participants at once, shows a statistically significant spontaneous rotation coefficient of 0.0068 for the head and of 0.0006 for the shoulders. Second, although the individual spontaneous rotation coefficients were small (all but two were smaller than 1%), in case of head rotations 15/19 (79%) participants had a statistically significant linear relationship between maximum rotation and deviation angle. In case of shoulder rotations, on the other hand, only 4/19 (21%) participants had significant fits to the model. Given that only a few participants executed significant shoulder rotations, we carried out the rest of rotation analyses only for head movements.

Analysis of Rotation Axes Along with the spontaneous rotation coefficients, our analysis also yielded an axis of rotation for each subject, separately for the head and the shoulders. Fig. 5 shows these axes, as unit vectors (the vector $\hat{\mathbf{a}}$ in our regression model), for the head rotations of the 15 participants whose regression analyses yielded significant results. The meaning of each of these vectors is as follows: it is the axis that maximizes the correlation between a participant's rotations and the corresponding values of the deviation angle.

Fig. 5 also shows the mean head rotation axis over all of these participants, equal to (+0.13, −0.65, +0.75). The axes of the fifteen participants are rather tightly clustered around this mean; the mean difference between the individual axes and the mean axis is only 24 deg. The largest contributions to this mean rotation axis come from the *Z* and *Y* axes. The signs of the components in this vector mean that for *positive* values of the deviation angle, participants tended to carry out rotations about the *positive Z* axis (head turned to the left, as seen from above, see Fig. 6 B) and the *negative Y* axis (head inclined to the left, as seen from behind, see Fig. 6 D); for trials in which the deviation angle was negative, on the other hand, the rotations tended to be in the opposite direction. We will return to the significance of these axes of rotation in the Discussion.

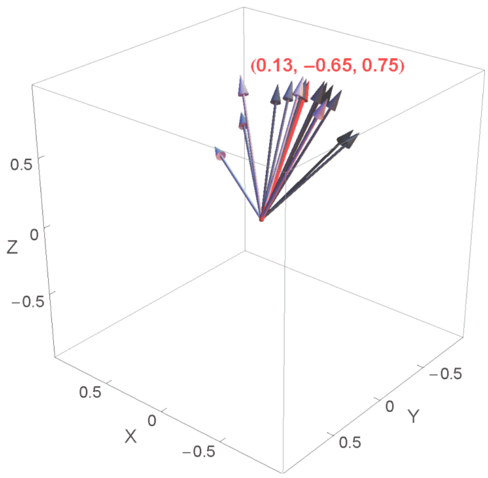

Figure 5: Individual head rotation axes represented in the space of rotations, shown in gray, as well as their mean, shown in red. The individual axes are shown in shades of gray that correspond to the value of the spontaneous rotation coefficient (the darker the arrow, the higher the corresponding coefficient). The three euclidean coordinates represent the mean axis. Given our regression model, the axes change to opposite directions for negative deviation angles.

Analysis of Translations The statistical analysis here is the same as for rotations. The mean spontaneous translation coefficients for the head and shoulders are respectively 0.012 ± 0.017 (± between-subject SD) and 0.008 ± 0.016. The translations of 7 (37%) and 6 (32%) out of 19 participants, for respectively the head and shoulders, were significantly correlated to deviation angle (bootstrap with 10^4 resampled datasets, $p < 0.05$).

Discussion

When asked for directions some people execute spontaneous incipient body movements. If a geometrical relation were found between represented spatial self-displacements and co-occurring incipient spontaneous body movements, it would be indicative of the implication of motor processes (motor plans or efference copies) in our spatial task and consistent with the activation of a sensorimotor prediction mechanism in solving spatial updating problems. Based on findings of the studies on spatial perspective-taking, we focused on the study of the imagined rotations and the angular disparity effect.

We devised a spatial updating task (see Methods and Fig. 1). In addition to behavioral data, we measured the spontaneous movements of our participants. To our knowledge, spontaneous movements have not been quantified so far in a spatial updating task.

Our behavioral results replicate the studied angular disparity effect on task performance (see Introduction).

We found that 15 out of 19 (79%) participants executed spontaneous head rotations related to the task parameters (if we include translations, 17 out of 19 participants (89%) executed a statistically significant motion)—in spite of the ease of the task, as shown by low error rates. These rotations were very small in amplitude (typically below 2 deg). In most of the participants, the movements were too small to be seen, but could nevertheless be measured with the motion tracker, and their relationship to the task parameters shown using our analysis. Indeed, these miniature head rotations were reliably correlated to the deviation angle, but much smaller (typically less than 1% of the deviation angle).

The geometrically specific correlation between spontaneous head rotations and the deviation angle has two aspects. First, larger deviation angles (corresponding to more difficult trials) led to larger rotations. Second, opposite deviation angles led to head rotations in opposite directions about a specific rotation axis, that we calculated using our linear model in rotation space.

The mean axis of rotation, averaged across participants, has a main vertical *Z*-axis component (i.e. a head turn, see Fig. 6 A, B) and a strong but lesser front-back *Y*-axis component (Fig. 6 C, D): the resulting head movement is thus a horizontal rotation of the head with an important tilt component. These head rotations are as if participants were trying to align themselves with the imagined orientation on the map. In the case of the front-back *Y*-axis, this alignment is in the image plane; in the case of the vertical *Z*-axis, it is as if the participants back-projected the vertical image onto the ground plane, and then tried to align themselves with the imagined orientation in this projection.

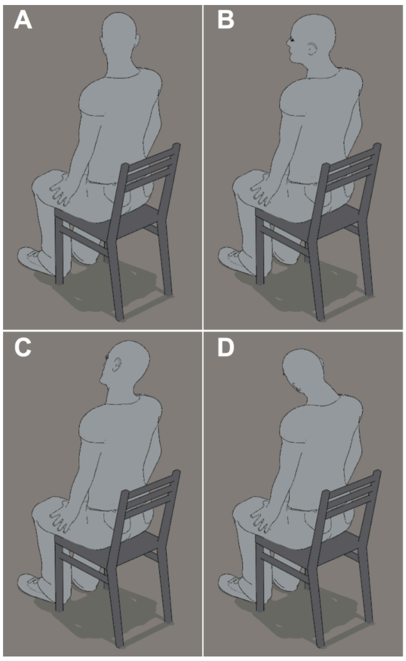

Fig. 6: The main component axes of average spontaneous head rotations. (A, B) Head turn about vertical Z axis. (C, D) Head tilt about naso-occipital Y axis.

Our findings on spontaneous head rotations are consistent with a motor contribution to spatial-updating task performance and with our action inhibition hypothesis as the characteristics of the spontaneous movements are geometrically consistent with those of actual rotations in the ground plane or image plane that would be required to bring the participant into alignment with the required initial orientation. We may speculate on several types of contribution. The premotor cortex could prepare an actual movement, which would lead to two separate processes: an anticipation process that predicts the outcome of the action (i.e., the map with the you-are-here street aligned with the participant's vertical axis) from an efference copy of the motor command, and the execution of the overt motor action, which would be inhibited at early stages (earlier for some participants than for others).

Alternatively, the implication of the motor system may be *epiphenomenal,* related to concurrent cognitive processes but not causally so.

We cannot at this stage answer the question of causality of the spontaneous movements. To settle this argument, we need a new experimental setting contrasting a condition in which movement is allowed or facilitated with another one where movement is restrained. It will allow us to measure the impact of each condition on the task performance and shed more light on the causality of the motor processes in mental spatial updating tasks.

Acknowledgements

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