

Statistics Predict Kinematics of Hand Movements During Everyday Activity

Harm Slijper¹, Janneke Richter¹, Eelco Over¹, Jeroen Smeets², Maarten Frens¹

¹Department of Neuroscience, Erasmus MC, Rotterdam, The Netherlands. ²Faculty of Human Movement Sciences, Vrije Universiteit, Amsterdam, The Netherlands.

ABSTRACT. Bayesian decision theory suggests that the statistics of an individual's actions (prior experience) play an important role in motor control and execution. To elucidate this relation, we recorded 7 million mouse movements made by a group of 20 computer users across a 50-day work period, allowing us to estimate the prior distribution of spontaneous hand movements. We found that the most frequent movements were in cardinal directions. The shape of this distribution was participant-specific but constant over time and independent of the computer that the participant used. This nonuniform directional distribution allowed us to predict systematic errors in initial movement directions, which matched well with the actual data. This shows how movement statistics can influence hand kinematics.

Keywords: arm movement, Bayesian statistics, computer mouse, kinematics, motor control

The body of literature focusing on the kinematics of target-directed arm movements is vast—a search of PubMed using kinematics and arm movement as keywords yielded more than 1,500 relevant hits. Among others, general characteristics of movement times and amplitudes (Fitts, 1966), curvature (Flash & Hogan, 1985; Wolpert, Ghahramani, & Jordan, 1994), movement variability (Haggard & Richardson, 1996; van Beers, Haggard, & Wolpert, 2004), movement direction (Baud-Bovy & Viviani, 2004; de Graaf, Sittig, & Denier van der Gon, 1991), and relations among these descriptors (Gottlieb, Song, Almeida, Hong, & Corcos, 1997; Smeets & Brenner, 1999) have been extensively described.

Recent theories of human perception and motor behavior have hypothesized that the found regularities are caused by the statistics of the visual world (like the distribution of fixation locations) and our motor repertoire (Purves, Lotto, Williams, Nundy, & Yang, 2001; Wolpert, 2007). This Bayesian approach (Kording, 2007; Kording & Wolpert, 2006) requires a thorough knowledge of the statistics of sensory input and motor output. For visual perception, measurements of specific parameters of images and scenes can be used to obtain reliable statistics (Foster, Amano, & Nascimento, 2006; Motoyoshi, Nishida, Sharan, & Adelson, 2007; Simoncelli, 2003).

There is, however, no easy way to determine the statistics of human motor performance. If studies are limited to short-term changes in instructed movements in a laboratory situation, the relevant statistics cannot be determined (e.g., Krakauer, Mazzoni, Ghazizadeh, Ravindran, & Shadmehr, 2006). Therefore, studies (Kording & Wolpert, 2006; Wolpert, 2007) have only been able to infer the statistics of

motor actions (referred to as priors) on the basis of observed movement variability within a very limited set of circumstances. Studies of natural, spontaneous arm movements over an extensive period of time have not been described (cf. Ingram, Kording, Howard, & Wolpert, in press). What amplitudes and directions are most commonly used? And are the movements straight? No knowledge about the statistics of such basic parameters is available.

To gain insight into natural movement behavior, we chose to measure computer mouse use because it is a frequently occurring type of arm movement that can be recorded without interfering with natural behavior. Using custom-built registration software, we registered mouse movements in a group of 20 computer users for a period of 50 workdays during real-life computer work. These movement trajectories were subsequently used to identify and characterize movement amplitudes, directions, velocities, and curvatures of more than 7 million naturally occurring arm movements. We will show that shape of the distributions of mouse amplitude and direction is similar across all participants, although highly participant-specific variations do exist (i.e., participants have a mouse signature).

To investigate how these movement statistics influence motor execution, we reasoned that the uncertainty regarding movement amplitude and direction decreases during movement execution. At the onset of the movement, there is significant uncertainty regarding the inverse kinematics and dynamics calculations needed to start a movement (Flash & Sejnowski, 2001) due to proprioceptive and visual errors (Smeets & Brenner, 2004; Sober & Sabes, 2005). In a Bayesian approach, this uncertainty is minimized by using prior experience (Kording & Wolpert, 2006). Moreover, Bayesian theory explains how this uncertainty (in terms of the likelihood) and the prior experience (the Bayesian Prior) are to be combined to minimize errors in endpoint direction. This would mean that the initial muscle activation chosen to start a movement would be influenced by how likely it was to make a movement in a particular direction. Such a control scheme implies that the initial movement direction for a certain endpoint direction can be predicted on the basis of the frequency distribution of endpoint directions. The advantage is that during the initial stages of the movement, execution

Correspondence address: Harm Slijper, Department of Neuroscience, Erasmus MC, Room Ee 1485, Dr. Molewaterplein 50, PO Box 2040, NL-3000 CA Rotterdam, The Netherlands. E-mail address: h.slijper@erasmusmc.nl

can be quickened by relying on the most common motor commands speeded-up. In this article, we will show that this is the case.

Methods

Participants and Data Acquisition

We installed custom-built registration software on the computers used by 20 participants, healthy employees (9 men, 11 women; $M \pm SD$ age = 33.9 ± 8.7 years) of the Erasmus Medical Center in Rotterdam, The Netherlands. Participants signed informed consent forms before entering the study. The participants performed a variety of computer-intensive work; 8 had administrative jobs, 6 were researchers, and 6 had managerial or other functions. Participants' monitors had an aspect ratio of 4 to 3. In all, 12 participants worked behind a monitor with a resolution of 1024×768 pixels, 7 worked with a higher resolution screen, and 1 worked with a lower resolution screen. Of the participants, each of 14 worked behind a single computer, whereas each of 6 worked with 2 different computers.

Participants were instructed to turn off the acceleration setting of the mouse and not to change the mouse gain during the measurement period. To establish how much the hand moved relative to the movement of the cursor on the screen, we had all participants perform a small calibration experiment in which they traced a square with a side of 3 cm on a piece of paper using the mouse. Across all participants, we found a gain of 197 ± 58 pixels/cm hand displacement.

The software registered the position of the cursor (x -, y -coordinates in pixels) with a frequency of 10 Hz and logged these data in the background to not interfere with the regular work of the participants. The unobtrusive nature of the installed monitoring software ensured that they quickly forgot that they were being monitored. It is unlikely that participants altered their working behavior as a consequence of participating in the study. Data were transferred automatically to a central server and processed offline (Slijper, Richter, Smeets, & Frens, 2007). To ensure that the data files (for each participant for every day) contained sufficient data, data files containing fewer than 10,000 position changes of the cursor (> 1 pixel) were not selected. For this study, we processed a random sample of 50 workdays for each of the participants.

Data Processing

Identification of Individual Cursor Movements

For each of the 1,000 recorded days, we extracted the times at which the cursor changed position. These time series, containing the corresponding displacements of the cursor in horizontal direction (x) and vertical direction (y), were used for further analysis.

To identify the start point and endpoint of cursor movements (see Figure 1A) from the recorded time traces, we calculated the (vector) combined displacement in x and y directions (xy). We considered as the *start point* of a cursor movement the sample after which the Δxy exceeded a

threshold. The *endpoint* was defined as the sample after which Δxy became subthreshold. We chose a threshold of 5 pixels/sample (approximately 0.25-mm hand movement) to ensure we could calculate movement direction accurately for small amplitude movements (because the screen forms a grid of pixels, only a small number of movement directions are defined for very small movements). By using a threshold of 5 pixels, we excluded only $10.7 \pm 2.4\%$ of the movements.

For every cursor movement, we determined subsequently the movement time, the amplitude (straight distance from start point to endpoint), and the endpoint direction. To estimate the magnitude of hand displacements (in cm) for the recorded cursor displacements, we divided the found amplitudes by the individual's gain factor from the calibration experiment.

For every working day and for every computer separately these values were used to determine individual usage patterns (see Figure 2).

Bayesian Predictions

To investigate whether the statistics of movement directions influenced the initial movement direction of individual movements, we analyzed movements for which this initial direction could be reliably determined. As our measurement method does not permit us to determine the direction of short movements, we restricted ourselves for this analysis to movements with amplitudes of at least 12 pixels and containing 5 data points or more (40% of the total number of movements).

According to Bayes's rule, the chance of a (initial) movement direction (φ_i) given the sensory estimate φ_e is described as:

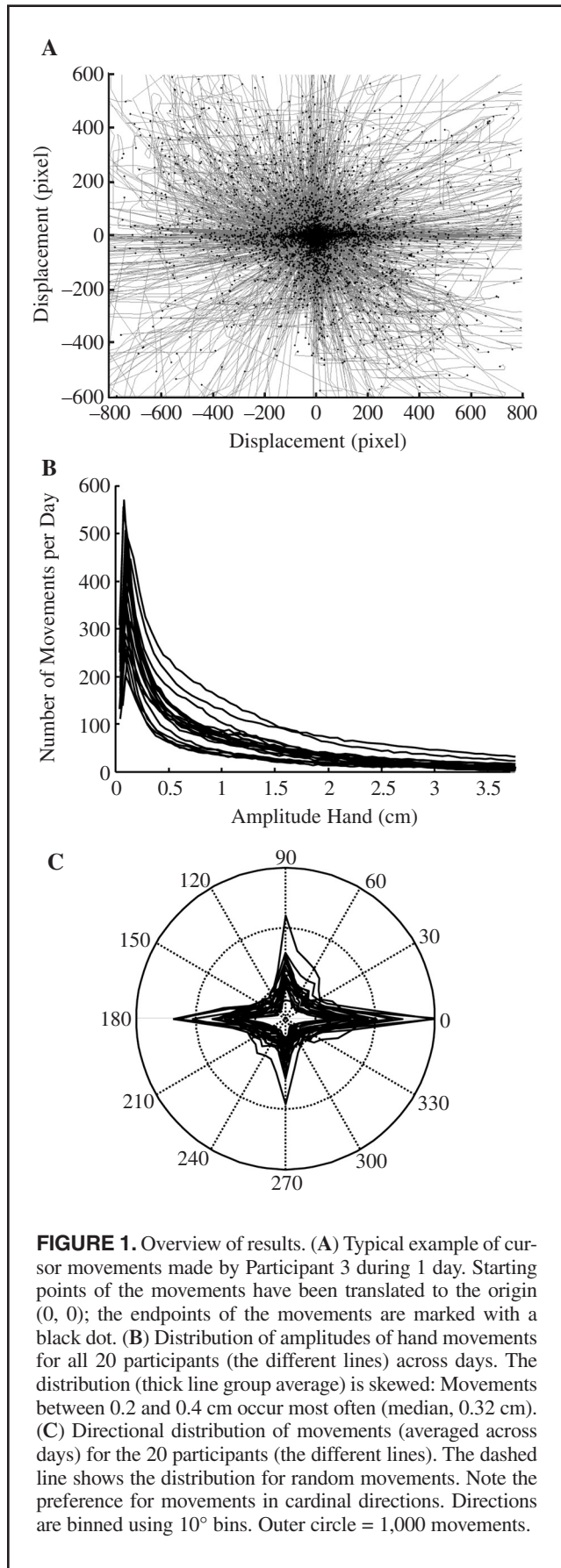
$$P(\varphi_i | \varphi_e) = \frac{P(\varphi_e | \varphi_i)P(\varphi_i)}{P(\varphi_e)}$$

where $P(\varphi_e | \varphi_i)$ is the sensory precision (given a direction φ_i , the chance that the sensory estimate equals (φ_e), and $P(\varphi_i)$ is the a priori chance for φ_i to occur. The chance $P(\varphi_e)$ is simply a normalization factor and does not change the relative probabilities between φ_e and φ_i . In the analysis, we modeled the sensory precision by a Gaussian distribution with $SD = 17^\circ$ and used the measured distribution of endpoint directions (histogram) as the prior.

To find the most likely value for the initial movement direction given a certain sensory estimate, φ_e (φ_e), we calculated the weighted average, or each value φ_i multiplied by its chance to occur:

$$\hat{\varphi}_i(\varphi_e) = \sum_{\varphi_i} \varphi_i P(\varphi_i | \varphi_e) = \sum_{\varphi_i} \varphi_i P(\varphi_e | \varphi_i) P(\varphi_i)$$

To compare this prediction with the actual relation between φ_i and φ_e , we calculated $\varphi_i - \varphi_e$ by the angle between a straight line distance between *start* (S) and *end location* (E) and the line from S to the *sample point* (M), where the distance between the trajectory and the straight line distance between S and E was maximal (see Figure 3). If the initial movement direction deviated in clockwise direction compared with the endpoint direction, the angle was denoted as positive.



Results

General Characteristics

On average, participants worked 8 hr and 29 min per day (computer on-off time). During this period, they made on average 7,192 (± 1967 ; *SD* between participants) cursor movements with a total duration of 1 hr and 12 min (± 23 min). During a day, the cursor followed a path of more than 1.5 million pixels ($\pm 480,580$), corresponding to approximately 74 m of hand movement.

Figure 1A shows an example of the displacements during cursor movements made by 1 participant during 1 day of work. We translated the starting location of each movement to the origin (0, 0). Note the nonuniform distribution of movements and the abundance of horizontal and vertical movements. This was not a specific characteristic of this participant but was true for all participants (see Figures 1B and C, compare the different lines).

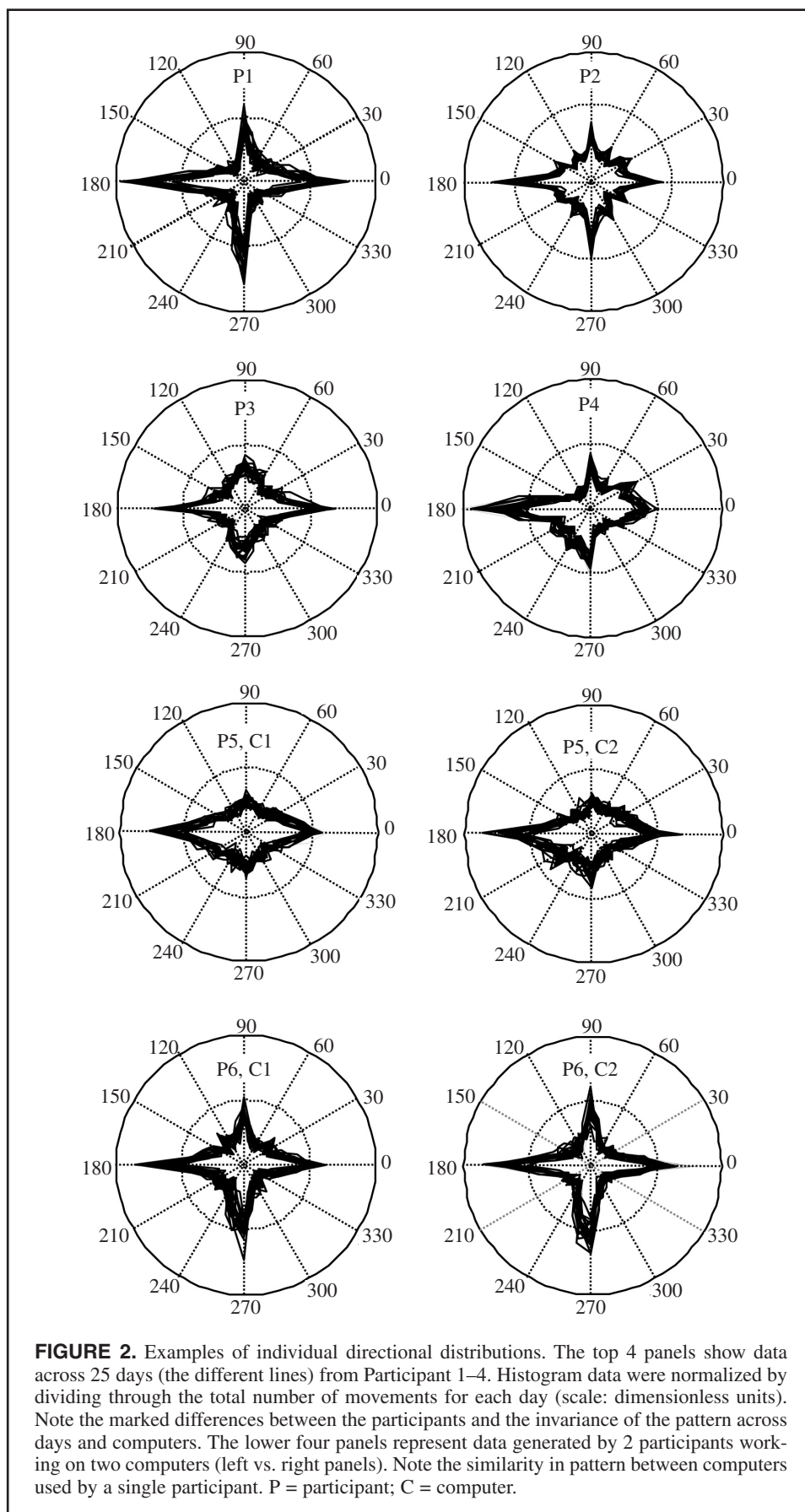
The average median amplitude of the hand movements was 0.32 ± 0.08 cm (corresponding to 62 ± 15 pixels of cursor movement). Shown in Figure 1B is the amplitude distribution of the hand movements for all the participants. The average median duration of the movements was 0.29 ± 0.05 s. Additionally, we found that the movements had a low average velocity (path length divided by the duration). The distributions of the average velocities showed that the majority ($> 50\%$) of mouse movements were performed with a hand velocity smaller than 1 cm/s.

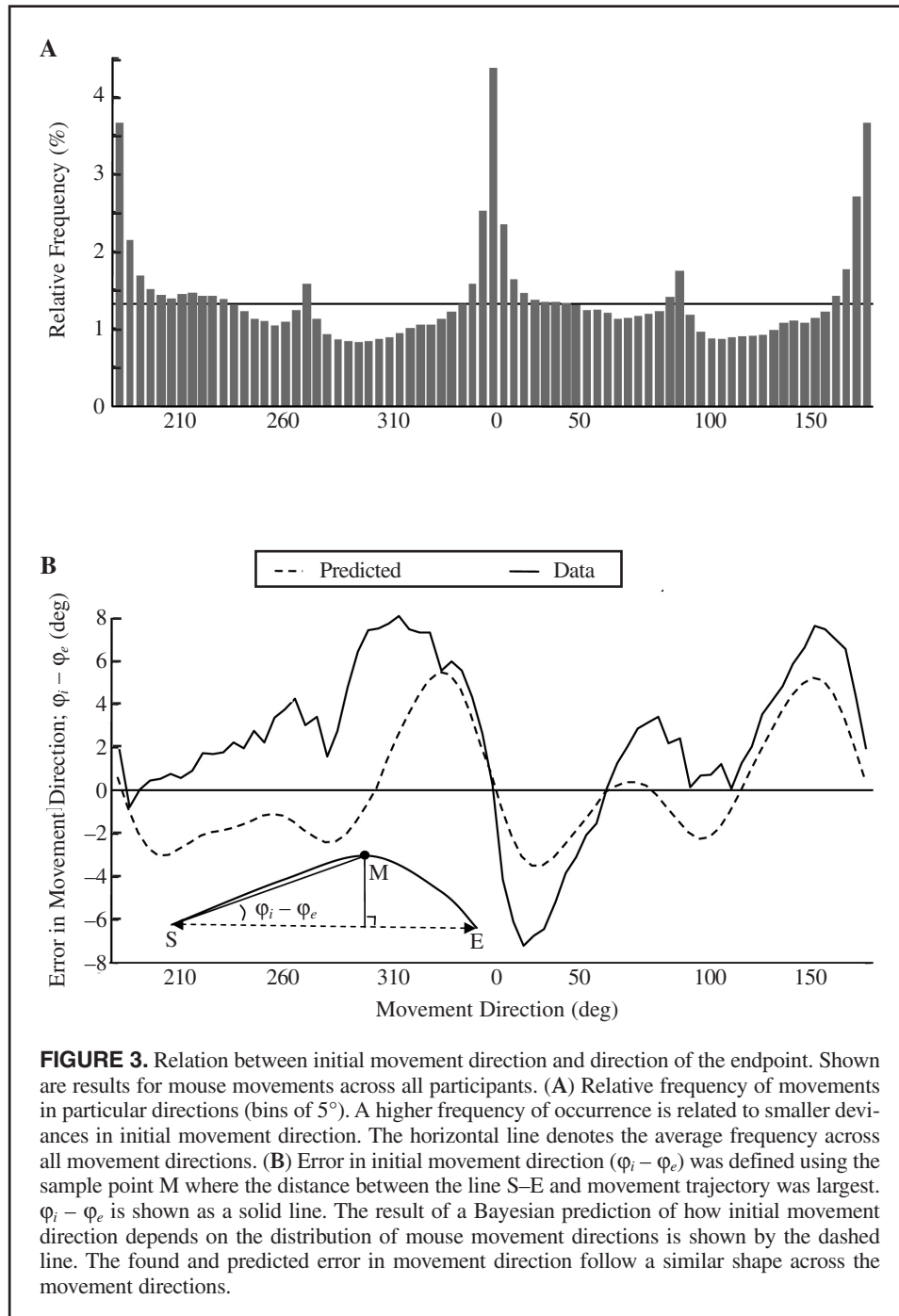
Distribution of Movement Directions

The preference for movements in cardinal directions on an average day for each of the 20 participants is shown in Figure 1C. Horizontal and vertical movements are most common in all participants. Almost half the movements (47.5%) were horizontal (within 22.5° from 0° [right] and 180° [left]), and 27% were vertical (within 22.5° from 90° and 270°). Figure 1C shows that the directional patterns for different participants (the different lines) are quite similar. Note that horizontal and vertical cursor movements correspond to hand movements to the left and to the right and away and toward the body, respectively.

Variability in amplitude between individual movements (reflected in the coefficient of variation across all directions and participants) was on average 13% larger for diagonal directions than for cardinal directions.

When we looked into the data of individual participants in more detail, we found that the directional pattern was surprisingly invariant across days and that there were idiosyncratic differences between the participants (see Figure 2). For instance, the difference in number of horizontal and vertical movements is much larger for Participant 1 than for Participant 3. Similar distinctive patterns were found in all other participants. Such differences are not due to differences in hardware, as the directional pattern was also invariant across computer used for participants who worked on more than one computer (see data of Participants 5 and 6 in Figure 2).





Predicting Initial Movement Direction

Initial movement directions deviated systematically from the direction of the endpoint of movements. Averaged across all participants and days, these errors were up to 8°, depending on the movement direction (See Figure 3, solid line). It is interesting that the directional error changed sign at the peaks in relative frequency (0° and 180°; Figure 3) or was very close to zero (at 90° and 270°) and that the slope of the curve was positive. In other words, the movements that occurred most often were those that had the smallest error in initial movement direction, and movements that

had endpoints close to these frequently occurring directions were biased to these directions.

Using Bayesian inference, we made a prediction of how initial movement direction would deviate from the direction of the endpoint, on the basis of how often movements occurred in specific movement directions, as previously mentioned in the introduction. Figure 3 (dashed line) shows the results of this prediction. After averaging the predicted values across all participants, we found a highly significant correlation of 0.703 ($p < .0001$) between the predicted errors and the found errors in initial movement direction.

Note how the data follow the shape of the prediction across all movement directions. The quality of this correspondence varied per participant, but we found a positive correlation for all 20 participants (on average, 0.44 ± 0.20 ; $p < .01$).

Discussion

Directional Pattern of the Mouse Movements

An important finding of the present study is that participants have strong directional preferences when making mouse movements. That is, movements in cardinal directions occur more often than diagonal movements (see star shapes in Figure 1C and Figure 2).

At least two factors might explain such preferences: (a) the structure of the visual field (here the computer–user interface) and (b) factors involving the motor control system (i.e., biomechanics and the visuo-motor transformation). The structure of the visual field has a large influence on the direction and amplitude of target-directed eye movements (saccades; Hooge, Over, van Wezel, & Frens, 2005), which are likely to precede the majority of mouse movements. Moreover, during computer use, the visual field also directly evokes certain motor performance, because many of the objects on the screen are interactive. That is, they allow the participant to click, select, move, or drag visual objects by using the mouse.

Over (2007) showed a preference for horizontal and vertical eye movements in tasks where the participant is to search for a target within a rectangular field. That is, participants' eye movements tend to follow luminance edges surrounding the workspace. A similar effect could occur for mouse movements. Because the user interface of most computers consists of rectangular elements organized in rows and columns (lists, menus, tabs, fields, buttons, etc.), it would provide a large number of horizontal and vertical lines that could induce a preference for mouse movements in cardinal directions.

Although the directional pattern across participants looked quite similar (Figure 1C), the pattern also seemed to contain some idiosyncratic characteristics that were specific for the individual user (see Figure 2). Thus, it seems that individuals have a *mouse signature*, or a typical way in which they move their mouse. It is likely that idiosyncrasies of the used software, such as the characteristics of the user interface of different programs, influence a participant's movement pattern in subtle ways, giving rise to reliable interindividual differences as observed in the directional distributions of the movements. Further study is needed to determine whether this signature is more indicative of which software a participant uses or which participant uses particular software. Either way, it is important to notice that these small amplitude movements, occurring thousands of times each day, compromise our exposure and are therefore a prior for future movements.

A second factor that might underlay directional biases is a mechanical one. Because different joint motions are

involved when moving in different directions, the inertia of the arm is not equal for all directions (inertial anisotropy; Flanagan & Lolley, 2001; Gentili, Cahouet, Ballay, & Papaxanthis, 2004; Sabes, Jordan, & Wolpert, 1998). Maximum inertia is commonly seen for movements in the sagittal direction (movements that would be vertical on the computer screen) because of larger motion in the elbow and shoulder. This effect might explain the preference for horizontal cursor movements over vertical cursor movements, but not the preference for the cardinal axes over the diagonals. Control schemes based on the optimization of variables related to inertial properties of the arm seem therefore unlikely to be able to explain the observed directional preferences. Moreover, it is not very likely that this factor has a large influence because of the low velocities (and thus low acceleration) of the movements.

We have found that initial movement errors were largest for diagonal directions (see Figure 3), that the error in initial movement direction depends on the direction of the endpoint, and that amplitude variability was largest for diagonal movements. These findings are in line with several experimental studies using relatively large arm movements (30–40 cm). Movements in oblique directions have the largest error in start direction (de Graaf, et al. 1991), have the largest endpoint errors without visual feedback (Baud-Bovy & Viviani, 2004), and are more curved (Smyrnis, Mantas, & Evdokimidis, 2007).

Several studies have assumed that these directional biases originate in a distorted internal representation of target direction. The present data show that such a distortion may originate partly from the statistics of our actions. Using a Bayesian approach (Ghahramani, 2000; Kording, 2007), we showed that directional distribution of movements could be regarded as a prior for the initial movement direction. For instance, we found that movements slightly above or below the horizontal direction had an initial movement direction along the horizontal direction in line with the high occurrence of these movements. This could mean that participants move in a direction in which they are likely to make the least movement error. However, mouse movements are not totally unconstrained. Usually movements are made toward a target, which can have any location relative to the current cursor location. Most movements will thus require a movement in a specific movement direction, so that moving in the direction in which the individual makes the least error will therefore not be effective.

Alternatively, the results we obtained could be explained by using an optimization approach (Ghez, Hening, & Gordon, 1991), for instance, by minimizing jerkiness of the movement trajectory or energy expenditure. However, it will be difficult to find a cost function that can explain the large (on average up to 8° ; see Figure 3) deviations in start direction, because highly curved trajectories are likely to cost more than straight trajectories.

Moreover, because the prior that is used in the Bayesian statistics method is known and the cost function that is used in a cost function analysis is an unknown, the most obvious

method to model our mouse movement data is to use Bayesian statistics. Therefore, a more likely explanation would be that individuals used prior experience and used this information to optimize the probability of moving in the right movement direction. Therefore, the statistics of individuals' actions influence movement execution: The more often movements are made in a particular direction the more likely the initial movement will point in that direction.

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