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Timing strategies underlying motor planning: the use of motor imagery

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Contents

Introduction

Human movement execution requires consideration of both geometry (the path it follows) and timing (the velocity profile along this path) an end effector follows. How the central nervous system selects geometry and determines timing is still unclear, but the concept of invariance can shed light on both aspects of movement generation. The influence of path's geometry on timing is best exemplified by the *two thirds power law* [Lacquaniti et. al., 1983], $v = \gamma\kappa^{-1/3}$. This rule of motion is an example of invariance, because motion satisfying the two thirds power law is a motion whose equi-affine velocity is constant ([Pollick & Shapiro,1996], [Flash & Handzel, 1997]) . Equi-affine geometry is not the only geometry that plays a role in movement generation [Bennequin et. al., 2010], but it certainly is the most robust example of invariance (evidence supporting the two thirds power law was found in eye pursuit [de'Sparti & Viviani, 1997], gait [Hicheur et al., 2005], leg motions [Ivanenko et. al., 2002], speech [Tasko et. al., 2004] and in visual perception of motion [Viviani and Stucchi, 1992]) .

The two thirds power law can be explained from two opposing perspectives. On one hand bio-mechanical explanations were provided as plausible causes for the emergence of this law. The two thirds power law may be a by-product of oscillatory movement generators in joint space [Schaal and Sternad, 2001] or may arise as a result of limb dynamics or muscle's mechanical properties [Gribble and Ostry, 1996] . On the other hand, the two thirds power law may reflect a central phenomenon, arising due to the inherent encoding of trajectory planning within the central nervous system. This is supported by prior evidence that has indicated that the encoding of kinematic features of hand trajectories is reflected by the variations in size and direction of the neuronal population vector representing the activities of a large population of cells within the primary motor cortex and other cortical areas [Schwartz and Moran, 2000]. Additionally, as was shown by a recent fMRI study [Dayan et al., 2007], the visual perception of motion of a dot moving along elliptical trajectories according to the two thirds law seems to evoke wider and stronger brain responses than the perception of movements complying with other laws of motion.

Motor imagery refers to the process of mentally simulating a motion without executing it. We assume (following [Jeannerod, 1995]) that motor imagery is functionally equivalent to the covert part of movement generation, without the following overt action. This assumption implies that the rules governing the kinematics of movement production should also apply to motor imagery. This was shown to be the case for Fitts's law [Decety and Jeannerod, 1995]. The assumption that the total durations of imagined and actually generated movements are similar (see [Guillot et. al., 2012] for a review) was well examined and was generally found to be valid (some interesting exceptions are described in [Rodriguez et al., 2008]). However, the well understood intermediate timing of movement production (such as the two thirds power law) has had a little matching evidence as far as motor imagery is concerned. Even the recent work by [Papaxanthis et. al., 2012] which directly examined the two thirds power law in motor imagery employed the same indirect strategy of comparing global movement durations of imagined and generated movements and based on those observations, made inference with respect to the internal strategy used by the subjects. In the present study we present a more direct paradigm for examining the kinematics of internally imagined movements. Applying this paradigm we present evidence supporting the notion that the velocity profiles of imagined movement trajectories are non-Euclidean, similarly to those of movement production. Our findings support the central origins of the two thirds power law and our methods open a new frontier of addressing the timing and geometry of continuous movements during motor imagery.

Methods

Participants and settings

53 healthy subjects (19 males and 34 females, ages 18-33) participated in a three hour experiment including imagery, drawing and questionnaires.

All subjects gave their informed consent and were paid for participation.

Subjects sat in front of a WACOM tablet placed on top of a 100 cm high table. The tablet's surface was tilted to 65 degrees from the horizontal plane. Subjects adjusted the chair height, the distance from the tablet and the keyboard location to a comfortable position. The subjects held a pen in their right hand and had their left hand being placed on the keyboard. Templates displayed on top of the tablet included an ellipse ((ELL), radii 14 and 3:5 cm with major axis directed at 45 degrees), two limaçons (with ratios of 1:3 (L13) and 2:3 (L23) between the arc lengths of their inner (smaller) loop and outer (larger) loop, scaled bigger by a ratio of 1.7 than the limaçons used in [Viviani and Flash, 1995]), and a circle (radius 10 cm, (CIR)). A red mark was displayed on the figural forms (on the top right extremity of ELL and on the rightmost extremity of the other templates).

Data acquisition paradigm

During imagery recording, each subject imagined drawing a single shape for 1 training session and 4 recording sessions containing 30 trials each were conducted. We instructed the subjects to keep a constant pace of about 3 to 4 seconds per lap, to avoid moving their right hand (which they imagined to be moving), and to discard any trial that they were uncertain of its quality being good enough.

All imagery trials contained a complex task aimed at extracting the duration and extent of a segment as well as the duration of a full cycle for imagery of the figural form (see figure 1). The subjects watched the template, which was displayed on the tablet with a red dot marking the cycle start. Then an auditory cue was played and the subjects closed their eyes and imagined a clockwise movement at a constant pace. Each time the imagery movement passed through the red dot, the subjects pressed a key with their left hand. At a random time another auditory cue was played. The subject memorized the imagined arm position at that time and continued the imagined movement and actual key pressing. Two more laps after the auditory cue a third longer auditory cue was played, and the subjects stopped the imagined movement and opened their eyes. The subjects marked on the screen the memorized position that his imagery trace has reached at the time of the second auditory cue, unless any interference to their memory or pressing has occurred. In this case, the subjects marked a box on the upper right corner of the screen to discard this record. Each trial consisted of the above measurement process and was followed by a short resting period.

The above description is for the main experiment (referred to as MEM), during which the subject had to memorize the imagined position at the time of the second auditory cue for 2 laps. We conducted another version of the experiment that served as a control for testing the involvement of memory in the experiment (referred to as NO MEM). This version differed from the MEM experiment by the fact that upon hearing the second auditory cue the subjects immediately opened their eyes and marked their hand's imagined position on the tablet, without continuing imagery motion.

During the trials involving the recording of actual hand trajectories (referred to as DRAW), the subjects drew the same template they have used for imagery. There were 2 sessions of the DRAW task, each composed of 6 trials of 6 laps each (all together 36 repetitions).

The subjects were instructed to draw as continuously and as smoothly as possible, to keep a constant pace while drawing and not to pay attention to the precision of their drawing.
The subjects rapidly traced the shapes with their right hand and opened eyes, and key pressed with their left hand each time the pen passed through the red dot marking to starting location.

The subjects were also asked to take the Edinborough questionnaire [Oldfield, 1971], and the MIQ-RS questionnaire [Gregg et al., 2010] and a follow up questionnaire in which the subjects reported, only for the imagery task, whether they have moved any of their body parts.
The drawing part, the follow up questionnaire and the MIQ-RS questionnaire were always administered after full completion of the imagery task. Subjects were instructed to never actually draw the shape prior to the completion of the imagery part of the experiment. This was done to prevent influence of prior execution on the imagery task.

Subject's selection protocol

We eliminated data of subjects who failed to comply with one of the following four requirements. We excluded data of subjects whose number of non-discarded data points was smaller than 80, or their MIQ score was lower than 4, or their LQ score was ≤ 0.7, and of one subject who marked all but one of the marks on the outer part of the shape L23. After elimination the remaining data were comprised of 7,7, 8,3 MEM subjects and of 5,3,5,5 NO MEM subjects, for the ELL, L13, L23,CIR templates respectively.

Data correction and normalization

The imagery data collected for each trial included the duration of the entire lap containing the beep (T, for MEM only), duration of the entire lap prior to the beep (T_p) and the duration of the segment from key press to the beep (t). Also recorded were the constant arc lengths of the entire lap (S) and of the segments connecting the red dot marking the start point with and the point on the path which was closest to the mark produced by the subject (s). We calculated the normalized segment duration relative to the total duration of the same lap $\tilde{t} = \frac{t}{T}$, and the normalized segment duration relative to the total duration of the prior lap $\widetilde{t_p} = \frac{t}{T_p}$, as well as the normalized segment arc length $\tilde{s} = \frac{s}{S}$, all for each trial separately.

It is of importance that $\tilde{t}$, $\tilde{t}_p$ and $\tilde{s}$ are by definition all cyclic with a period 1, because our analysis considers only movement from the last passage through the starting point to the position of hearing the second auditory cue. By default the values of $\tilde{t}$ are taken within the range [0, 1]. As for the $\tilde{s}$ values, they were also taken to be within the range of [0, 1] except for two cases. If for a data point $\tilde{t} < 0.25$ and $\tilde{s} > 0.75$, we interpreted this as $\tilde{s}$ belonging within the prior lap (which indicates smaller discrepancy between $\tilde{t}$ and $\tilde{s}$), and took $\tilde{s}$ to be $\tilde{s} - 1$ which is in the range of [-0.25,0]. Similarly, if $\tilde{t}$> 0.75 and $\tilde{s}$ < 0.25, we took $\tilde{s}$ to be $\tilde{s} + 1$ which is in range [1,1.25].

For the self-intersection point of the limaçon shapes we removed all data points within a 1 cm radius around it, to avoid ambiguity in the interpretation of the location of the marked position as a point on the curve.

The drawing data included all trials of the second session, taking all but the first two repetitions and the last one (except for one repetition of a single subject which we manually removed due to an extreme deviation from the template). This left us with 18 laps for each subject.

Distribution analysis for $\tilde{t}$ and $\tilde{s}$

We calculated the data distribution of $\tilde{t}$ and $\tilde{s}$ within bins covering the range of [0.05,0.95]. We calculated the predicted distributions of $\tilde{s}$ based on two possible laws of motion: moving at a constant velocity or moving according to the two thirds power law. Each law of motion establishes a specific distribution of the predicted values of $\tilde{s}$, for each of the measured distributions of $\tilde{t}$. This prediction is done by using the normalized velocity profile defined by the law of motion. Integration of this velocity profile gives a prediction of a $\tilde{s}$ value for each value of $\tilde{t}$ and hence a distribution of $\tilde{s}$ values for each distribution of $\tilde{t}$ values. For each subject we compared his measured distribution of $\tilde{s}$ with his predicted distribution of $\tilde{s}$ (based on his measured $\tilde{t}$ values) using the χ^2 goodness of fit test, for each of the movement laws.

In order to present group data for all subjects for a single template (this was done for the MEM subjects only, both for MEM and for DRAW data, see figure 2.) the distributions of $\tilde{t}$ and $\tilde{s}$ were resampled such that the $\tilde{t}$ distribution will become uniform. The resulting resampled distributions represent the distribution of $\tilde{s}$ used by subjects, with the random effect of the $\tilde{t}$ distribution eliminated. Therefore these distributions can be compared to the $\tilde{s}$ predictions of the two power laws which assume $\tilde{t}$ is uniformly distributed. This resampling was done by repeating for 10000 times for each bin of the $\tilde{t}$ variable the process of randomly selecting one data point (meaning, a couple ($\tilde{t}$,$\tilde{s}$) with $\tilde{t}$ within the bin) from each bin and collecting the resulting $\tilde{s}$ values in a histogram for each template.

In order to qualitatively compare the extent to which each of the two laws of motion (the two thirds power law versus the constant velocity law) matches the measured data, we derived for each individual subject the likelihood ratio for the two predicted distributions, calculated as follows:

$$\ln \lambda = \sum_i d_i \ln P_i^{Eu} - \sum_i d_i \ln P_i^{EA}$$

where λ is the likelihood ratio, d_i is the number of observed data points in bin i, P_i^{Eu} is the number of data points predicted by to the constant Euclidean velocity law of motion ($\beta = 0$) and P_i^{EA} is the number of data points predicted by the constant equi-affine velocity model ($\beta = \frac{1}{3}$). The likelihood ratio test was performed by comparing λ to a χ^2 distribution with a 1 degree of freedom.

Estimating velocity profiles as power laws

In addition to analysis of distributions of marked locations we also look into the correlation between durations and location of each segment. We consider models of normalized velocity $\tilde{v} = \frac{d\tilde{s}}{d\tilde{t}}$ as power laws of the form $\tilde{v} = \gamma\kappa^{-\beta}$. We want to estimate β, which is the only free parameter of this model (because $\int_0^1 \tilde{v}\, d\tilde{t} = 1$, so γ is uniquely determined). We define an error term, the Cyclic Mean Squared Error (CMSE) in $\tilde{t}$ to be:

$$CMSE(\tilde{t}, \tilde{s}) = \sum_j d\left(f^{model}\left(\tilde{s}_j^{data}\right), \tilde{t}_j^{data}\right)^2$$

where $\tilde{t}_j^{data}, \tilde{s}_j^{data}$ are the measured data points, $f^{model}(s)$ is a function calculating predicted $\tilde{t}$ values for given $\tilde{s}$ values and for a given value of β, and $d(\mathrm{x}, \mathrm{y}) = min(|x - y|, 1 - |x - y|)$ is the cyclic distance (which we use due to the periodic nature of our variables). We use nonlinear regression to estimate the β values within the range of $[-1,1]$ by minimizing the CMSE error, along with confidence intervals for β using $p = 0.05$.

Results

Actual motion during imagery

During the imagery part of the experiments, the subjects kept their eyes closed and their right hand rested on the table. This was visually checked by the experimenter. Due to technical difficulties we have not recorded E.M.G. nor E.O.G.. Nine out of forty three subjects reported moving their right hand during the imagery trials (always reporting a total movement smaller than 5 cm). Five subjects reported moving their closed eyes but not their head. Five subjects reported moving their head but not their eyes. Nineteen subjects reported moving both. Two subjects reported moving the leg. One subject reported moving the tongue.

Distribution of subjects' marked locations

Data of two selected subjects for each template is shown in figure 4, accompanied by their matching $\tilde{s}$ distributions.

For each shape the observed grouped $\tilde{t}$ distribution and the observed grouped $\tilde{s}$ distribution were not uniform (based on a χ^2 goodness of fit results of $p \leq 0.001$ for each of the three shapes, checking for 18 bins of size 0.05 covering the range $[0.05, 0.95]$). The grouped resampled distributions of $\tilde{s}$ for MEM and DRAW are shown in figure 2. This figure shows that both the number of peaks and their location seem to fit well the two thirds power law, indicating that the subjects' tendency to move slower in the more curved segments of the shape is evident from the fact that the subjects stopped more often while passing through the curved regions of the shape. For the DRAW data the two thirds power law describes the data better than for the MEM data, which is not surprising given the much larger number of samples for the DRAW versus the MEM data.

For each shape the values of $\tilde{t}$ were used as inputs to the two power laws considered here, namely $\tilde{v} = \gamma\kappa^{-\beta}$ using the specific β values of 0 and $\frac{1}{3}$ corresponding to the constant velocity and the two thirds power law, respectively. For none of the two power law models the predicted distribution of $\tilde{s}$ matched the observed distribution of $\tilde{s}$ (based on a χ^2 goodness of fit results of $p < 0.001$ for each of the three shapes and each of the β values, using the same method). It is reasonable that even though there was no perfect match to the predicted distributions and the χ^2 goodness of fit test has failed, one of the two movement laws may still provide a significantly better explanation of the observed distributions than the other model. Hence for each subject we separately compared the outputs of the two power law models using the likelihood ratio test. We tested whether the $\beta = \frac{1}{3}$ model outperforms the null $\beta = 0$ model. We obtained significantly positive results for the majority of subjects for each of the templates (See the results shown in table 1, for both MEM $\tilde{t}$ data, MEM $\widetilde{t_p}$ data and NO MEM $\widetilde{t_p}$ data).

	Shape	$p < 0.05$	$p > 0.05$	Invalid	total
MEM, $\tilde{t}$	L13	2	4	1y	7
	L23	2	5	1 z	8
	ELL	2	5	0	7
MEM, $\widetilde{t_p}$	L13	0	6	1 ι	7
	L23	4	3	1 ɟ	8
	ELL	1	6	0	7
NO MEM, $\widetilde{t_p}$	L13	1	2	0	3
	L23	1	4	0	5
	ELL	2	3	0	5

Table 1: Single subject results of the likelihood ratio test: Number of subjects for each shape and p values range, calculated for 14 bins covering the range $[0.05, 0.95]$. Analysis of three data sets is shown in three corresponding rows. The first (MEM, $\tilde{t}$) row shows to the MEM subjects, with time normalization done in respect to the same lap. The second row (MEM, $\widetilde{t_p}$) shows analysis of the MEM subjects, with time

normalization done in respect to the previous lap. The third row (NO MEM, $\widetilde{t_p}$) shows to the NO MEM subjects, with time normalization done in respect to the previous lap (this is the only option for the NO MEM subjects, who do not complete the lap in which they are stopped by the beep).

For 4 subjects the test failed due to a technical problem– when there exists a bin which is predicted to be empty by the movement law yet it turns out to be nonempty in the observation, the likelihood ratio test forces a zero division. In this case we checked a different binning scheme, dividing the range $[0.05,0.95]$ to a different number of same-sized bins:
y. gave $p < 0.05$ value for the test on 12 bins, but failed the tests on 13 and 14 bins.
z. failed the test on bin numbers 11 to 18.
ι. gave $p < 0.05$ value for the test on 11 bins but failed on 12-18 bins.
ɿ. gave $p > 0.05$ value for the tests on 11,12,13 bins but failed on 14 bins.

Fisher's combined probability test gave a significant overall effect ($p < 0.001$ for each shape, for MEM $\tilde{t}$, MEM $\widetilde{t_p}$ and for NO MEM separately). Hence we see that the effect of curvature on the subjects' marked positions is robust to the choice of a normalization procedure and is also independent of the effect of memory. These results therefore indicate that the number of marked locations within each bin is correlated with the curvature of this location on the template. The number of marked locations is an indication of the velocity of the imagined movement, because the probability of being stopped within a specific bin is directly related to the time the subject has spent imagining movement within this bin, which is inversely related to the velocity. So a correlation between velocity and curvature is evident in our data. This correlation is interpreted as providing evidence in support of our hypothesized model, namely the two thirds power law.

Using a similar likelihood ratio test for distributions we also compared how the MEM $\tilde{t}$ data fits the two thirds power law of motion ($\beta = \frac{1}{3}$) compared to the best of three alternative models ($\beta = \frac{2}{3}, 0, -\frac{1}{3}$). For 3,3,3 out of the 7,8,7 MEM subjects of L13,L23,ELL respectively, the test gave statistically significant ($p < 0.05$) results, indicating that the two thirds power law is the best descriptor of motion for the respective subject.

Quantitative analysis of power laws for drawing and imagery

For the drawing and imagery data of each subject we performed the nonlinear regression procedure, obtaining optimal β values as well as confidence intervals for $p = 0.05$. The resulting estimations of optimal p values as well as confidence intervals for these estimations are shown in figure 3. Unlike the distribution analysis this analysis takes advantage of the pairing of the $\tilde{t}$ and $\tilde{s}$ variables which allows matching a velocity profile and not merely a distribution of values.

For the DRAW data all subjects had a confidence interval for $p = 0.05$ contained within the range $0.08 \leq \beta \leq 0.58$. For each shape the mean of optimal β values across MEM subjects were $0.38;\ 0.31;\ 0.28$, and the mean across NO MEM subjects of optimal β values were 0.33,0.38,0.33, both for L13, L23 and ELL templates respectively.

For imagery MEM 4,1,7 out of the 7,8,7 L13,L23,ELL subjects respectively had a confidence interval contained within the range $0.1 \leq \beta \leq 1.1$. For each shape the mean across MEM subjects of optimal β values were $0.33;\ 0.28\ (0.04);\ 0.72$ for L13, L23 (L23 excluding the 8th subject) and ELL templates, respectively.

For imagery NOMEM 0,0,4 out of the 7,8,7 L13,L23,ELL subjects respectively had a confidence interval contained within the range $0.1 \leq \beta \leq 1.1$. For each shape the mean of optimal β values across NO MEM subjects were 0.18,0.24,0.78 for L13, L23 and ELL templates respectively.

Discussion

Our results demonstrated how the local velocity of continuous imagery drawing movements depends upon local curvature of the imagined shape. We found out that the two thirds power law is a better description of the observed normalized location distributions than movements with a constant Euclidean speed. We also estimated β

values for the power law and those had a strong tendency for positive values, with group means of 0.18 to 0.78. Overall, these results suggest that the source of the two thirds power law is in the planning stages of motion and that this law is not only a byproduct of motor execution. This joins a large body of evidence reaching a similar conclusion ([Cassile et al., 2010], [Schwartz and Moran, 1999], [Papaxanthis et al., 2012]).

Our observations suggest the two thirds power law has a central origin

For movement execution, the curvature-velocity relation can be well quantified as a power law (as seen in various studies, starting with [Lacquaniti et al.,1983], and reported for many end effectors, tasks and geometric shapes). A crucial question is to what extent the exponent of the power law, β, truly equals 1/3. This is important because $\beta = \frac{1}{3}$ implies a constant equi-affine velocity, suggesting that movement is planned in an equi-affine invariant manner. For production data the specific values of β seem to vary with age (see [Viviani and Schneider, 1995]), and in adults they are closer to $\frac{1}{3}$. Our nonlinear regression analysis of drawing agrees with such an analysis, giving mean group β values ranging from 0.28 to 0.38.

Our results demonstrate that a similar curvature-velocity relation strongly exists for imagery as well. This is evident from the distributions of the subjects' marked positions. A quantification of this relation using nonlinear regression seems to suggest that the group's mean β values are positive. However, the resolution of our data does not allow for a precise determination of the β values of imagery movements. It is known (see [Sternad and Schaal, 2001]) that using nonlinear regression to extract the β values gives results which diverge more from $\beta = \frac{1}{3}$ than using a linear fit in the log-log space. This means that our method of nonlinear regression is stricter than the standard methods commonly used in the motor control literature, which are inapplicable for our sparse imagery data which do not include well sampled velocity profiles.

A possible relation of the two thirds power law to biomechanical smoothing was suggested by [Gribble and Ostry 1996] who suggested that the two thirds power law may reflect smoothing by the low-pass filtering properties of muscles. However, such smoothing properties of muscle activations are unlikely to contribute to our observations due to the absence of actual motion during imagery.

As to the possibility that the two thirds power law may result from movements being produced as oscillatory movements in joint space (see [Schaal and Sternad 2001]), the difficulty in using this explanation to account for our findings is that one has to assume that the subjects' mental representations include a manner of using the imagery joint movements for the representation of the resulting movement in task space during movement imagery. In that case, the forward kinematics for an imagery arm, including its mechanical properties should have been well represented within the motor system and as a byproduct of this process a power law would have been observed in the imagined task space. Here again the justification for using this explanation to account for our findings which were obtained in the absence of actual motor action, is unclear.

Our paradigm extends the methodology of recent studies

The recent study by [Papaxanthis et al. ,2012] providing evidence for the two thirds power law appearance in imagery, is complementary to our current study. Nevertheless, the two studies differ along several significant aspects. Our paradigm allows one to measure the internal velocity profile of movement, providing a resolution inaccessible when relying upon measuring total movement duration, or durations of pre-specified segments defined by the experimenter. We strived towards a description of the internal temporal structure of a continuous motion. A methodology similar to ours [Rodriguez et al.,2009], showed that the velocity profiles of movement imagery for straight reaching movements did not follow the bell shape characteristic of actual movement for the same reaching tasks. Although at a first glance this may seem to be contradictory to our results, there is no inherent contradiction. That study emphasized that the failure is probably due to the fact that actual and imagined movements may have different durations during simple automatic tasks like reaching while such differences in durations may vanish in the case of complex attention demanding tasks (such as ours).

It was recently qualitatively shown that the cumulative turning angle $\int |\kappa| \, ds$ plays a role in determining the duration of motor imagery [Papaxanthis et al.,2012]. It is possible that the similarity in global durations between imagery and production reported there has more to do with the global properties of time allocation for motor tasks than with the local coupling between curvature and velocity, which is the essence of the two thirds power law. This global relation hints to a local curvature-velocity relation, but is by no means equivalent to it. It is worth mentioning that (starting with [Shepard and Metzler,1971]), a well-document relationship between the duration of imagined rotations (measured as a reaction time) and the angle of imagined rotations was reported for a variety of mental rotation tasks.

Another technical yet essential issue is that in order to study the two thirds power law we must limit ourselves to shapes whose curvature is never 0. The mathematical prediction of the two thirds power law is that along zero curvature segments the velocity should go to infinity. Unfortunately, the shapes used in [Papaxanthis et al., 2012], were composed of concatenated straight segments (whose curvature is 0), connected by curved segments of a constant curvature. Modeling of movement along such complex shapes may be done by models relating timing and geometries (such as the one proposed in [Bennequin et al., 2009]). However this is non-trivial, and will definitely require divergence from the two thirds power law during some sections of the movements. In addition the shapes used in that study [Papaxanthis et al., 2012], contained cusp points, ate which the subject had to stop and move back along the direction from which he has come (because each subject traced each shape 3 times in a sequence, so he had to pass, for example, from drawing a line from left to right to drawing it from right to left), for which the two thirds power law has no prediction.

Can motor imagery be used to detect motion segments?

Many studies looked into the question whether real and imagined movements have similar durations or to what extent the durations of motor imagery and production are positively correlated ([Guillot, 2012]). Consistent deviations from real-virtual isochrony (which is the common term in the imagery literature for description of this similarity, not to be confused with the usage of the word "isochrony" in the motor control literature) were reported to exist, and were attributed to several factors. Some such deviations seem to be due to non-proficiency in imagery skills, and diminish with the expertise of subjects in either motor imagery of the task or in the actual performance of the task. However, another kind of discrepancy between the durations of imagined versus executed movements may arise which may originate from an inherent difference between well performed imagery and production. In the cases that such differences are found they may provide useful information as to the characteristics and structure of the motor plan.

Assuming subjects follow a segmented plan (as in [Morasso and Mussa Ivaldi, 1982], [Viviani,1986],[Flash and Hochner, 2005],[Polyakov et al., 2009]) , it may prove that imagery tasks provide additional information of this plan. An important issue is peripheral smoothing effects which may cause a divergence of imagery segmentation patterns from those of production. Possibly other essential discrepancies in the manner the plan is expressed exist between imagery and production. Each such discrepancy may shed a new light on segmentation, revealing new aspects of motion planning unapproachable via the use of other paradigms.

Further analysis of continuous and discrete movements

The paradigm we described here is far from being exhausted. The appearance of Fitts's law in motor imagery [Decety and Jeannerod, 1995], followed by that of the two thirds power law, may lead to the question whether other rules of motion will also appear in motor imagery. For example, the minimum jerk model ([Flash &

Hogan, 1985]) has predictions with regard to both movement timing and movement geometry of movement which can be examined in motor imagery. A main benefit of imagery studies of kinematics can be that it may allow distinguishing between the properties of movement arising from feed forward trajectory execution versus properties of movement arising from online motor execution and feedback mechanisms. These major questions are yet to be resolved in future studies.

Figure 1: Experimental procedure

Each subjects preformed the experimental procedure on 1 out of the 4 templates (shown on the left), for 4 sessions each containing 30 trials (each trial is described in the middle). For each trial, one measurement of each of the 8 parameters (shown on the right) is recorded.

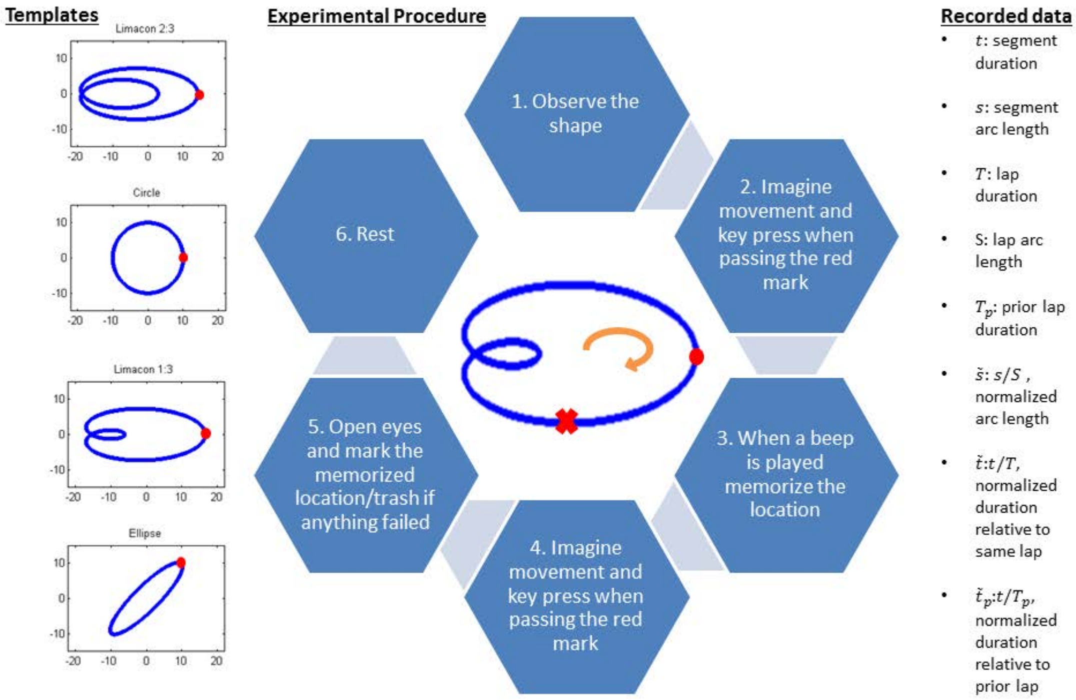


Figure 2: Group distributions of $\tilde{s}$

For each of the three templates, we show a resampled distribution of $\tilde{s}$ values (EXP), such that $\tilde{t}$ distribution is uniform, for imagery (upper row) and drawing (lower raw) data. Also shown are model predicted distributions for movement according to the two thirds power law (Model 2/3PL) and for movement with a constant Euclidean velocity (Model const v) assuming a uniform distribution of $\tilde{t}$.

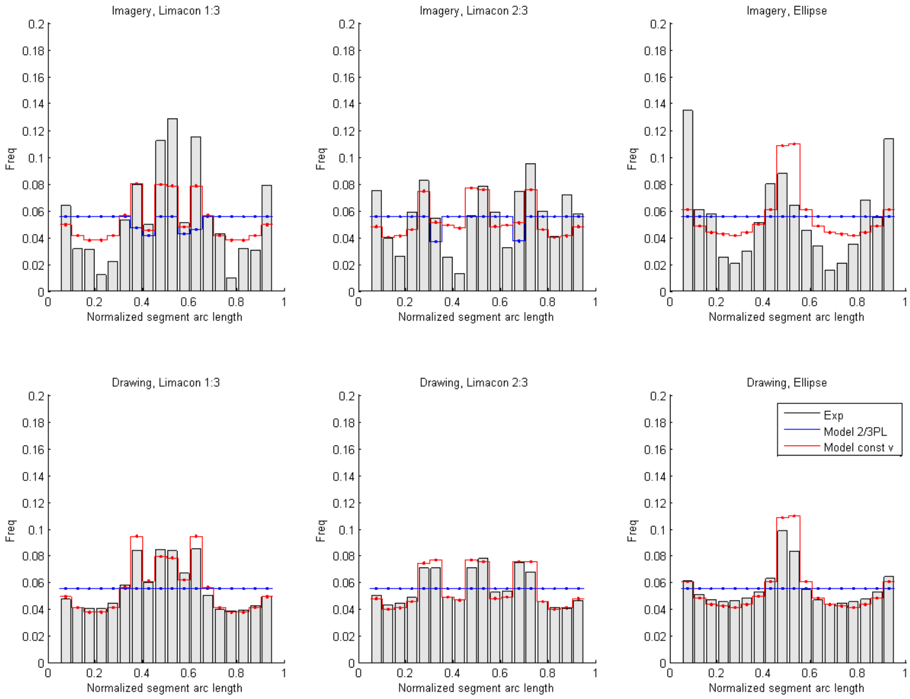


Figure 3: Nonlinear regression results for β

For each of the three templates and for each of the subjects we show the results of the β values derived by the nonlinear regression process along with confidence intervals for $p = 0.05$, for imagery (upper row) and drawing (lower raw) data. We separate MEM subjects (in blue) from NO MEM subjects (in black).

Also shown for comparison are the constant β values of the two thirds power law ($\frac{1}{3}$, dotted pink line) and of movement with a constant Euclidean velocity (0, red line).

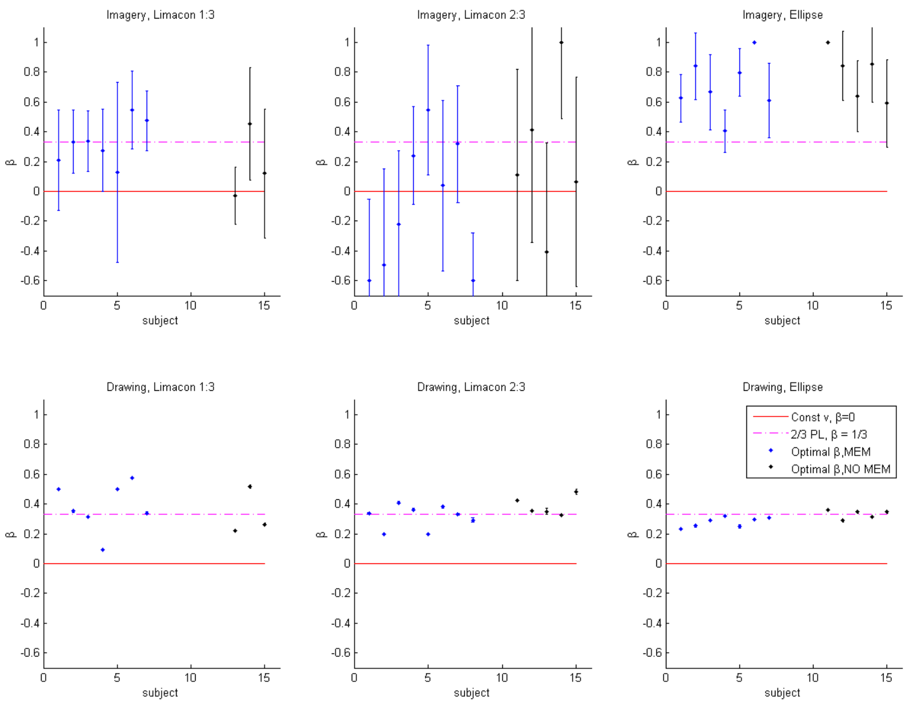
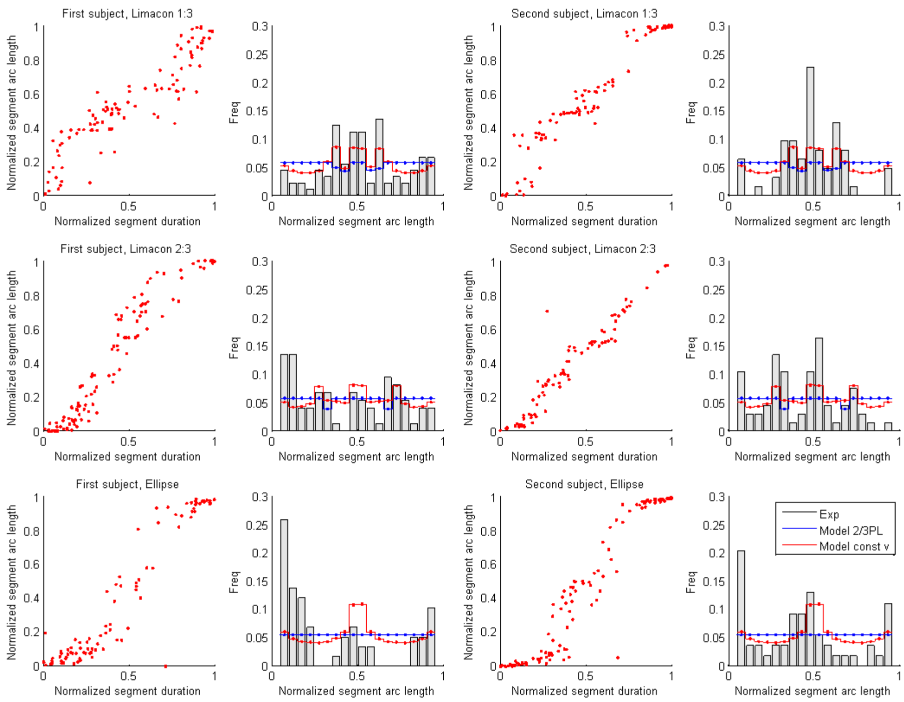


Figure 4: Single subject profiles and distributions

For two selected subjects for each template we show the subject's $(\tilde{t}\,,\tilde{s})$ profile (columns 1 and 3) along with a distribution of the subject's $\tilde{s}$ data. Also shown are model predicted distributions for movement according to the two thirds power law (Model 2/3PL) and for movement with a constant Euclidean velocity (Model const v), assuming a uniform distribution for $\tilde{t}$.



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