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Drifting towards a diffuse control model of exploratory motor learning: A comparison of global and within-trial performance measures

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Abstract. Accurate measurement is crucial for understanding the processes that underlie exploratory patterns in motor learning. Accordingly, measures of learning should be sensitive to the changes that take place during skill acquisition. Most studies, however, use trial-based global measures that assess performance but do not actually measure gradual changes taking place *within* trials. The present study attempted to remedy this shortcoming by analysing a visual adaptation task, and comparing traditional global measures of learning with new, within-trial measures. Movement time was the only global measure sensitive to changes in the movement trajectory during learning. Three new measures were expected to reveal changes to the movement trajectory that are associated with learning: (i) the length of runs, (ii) change of trajectory angle in relation to the target, and (iii) drift (change in distance from the target). All three measures were sensitive to learning and indicated a gradual straightening of the movement trajectories over trials. Furthermore, three different methods to partition trajectories into segments were examined. The new within-trial measures, irrespective of partitioning method, prove promising for the development of a diffuse control model of exploratory learning.

1 Introduction

The process of acquiring a new motor skill involves the coherent organisation of a number of component skills (e.g. perceptual, control, exploratory, and pattern learning). Although the literature describes many types of learning, measurement remains problematic. Traditionally, researchers have used global measures that associate learning with various performance characteristics (e.g. absolute error, movement time, and average speed) at the trial level. Trial-based global measures, however, are incapable of measuring any learning processes that may be occurring *within* trials. The inadequacy of trial-based measures is an enigmatic problem in assessing exploratory learning. Exploratory learning is perhaps the most fundamental and, at the same time, the least understood form of learning; it was first identified more than a century ago (Thorndike 1898), and is often labelled "trial-and-error" learning. It has been investigated across a wide variety of situations ranging from sensorimotor tasks to cognitive problem solving (De Jong and Van Joolingen 1998; Effken and Kadar 2001; Touvinen and Sweller 1999).

In the early stages of learning a motor skill, when learners have to adaptively integrate perceptual information with motor control, exploratory learning prevails. At that stage, learning can be regarded as a transition from highly unstable, exploratory movement trajectories to more stable and consistent movement patterns (Shaw et al. 1992). The assessment of exploratory learning requires analytic tools that are sufficiently fine grained to allow within-trial measurement. A more complete understanding of learning may be obtained by analysing not only the outcome of learning, but also the actual spatio-temporal changes in the movement patterns of interest during the learning process (Effken and Kadar 2001). Current learning measures are unable to quantify the seemingly random, meandering patterns associated with exploratory learning.

Recently, Effken and Kadar (2001) successfully applied a diffuse control model to describe the process of learning to run a haemodynamic system through a computer display. In the literature, diffuse processes are usually described in two different ways: (i) partial differential equations used to capture the deterministic nature of the global process, and (ii) statistical description that captures the nature of individual movement trajectory's randomness (random walks) (Berg 1983). Adopting the latter approach, Effken and Kadar (2001) used the statistical description of run lengths and directional changes during learning. Runs were mapped into a one-dimensional distribution on the basis of their length without measuring their distance from the goal, and directional changes were

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measured relative to the target. Their findings suggested that exploratory learning could be described as a random walk process with increasing bias (i.e. a diffusion process with increasing drift).

It appears that a diffuse control strategy, which capitalises on a certain degree of randomness (diffusion) mixed with increasing goal bias (drift), is surprisingly simple yet highly generic and efficient. An added advantage is that this model avoids the problem of interpretation in the currently popular fractional random-walk analysis (Mandelbrot 1982). Specifically, the interpretation of Hurst's exponent (Hurst 1951) in terms of memory and randomness (persistence versus anti-persistence) is problematic because this temporal correlation-based method is descriptive rather than explanatory (Peters 1991). Moreover, recent attempts to use fractional Brownian motion analysis in the context of human movement control has also been shown to be highly problematic because it relies on the controversial open-loop versus closed-loop distinctions (Reed 1982; Treffner and Kelso 1999). Significantly, the proposed diffuse control model has the potential to both replace the traditional trial-and-error model and become an explanatory model of exploratory learning.

The seemingly random, meandering patterns in various motor learning tasks may also be explained by such a diffuse control strategy. For example, Cunningham (1989) and Imamizu and Shimojo (1995) had participants master a perceptual-motor mapping involving rotation of vision. They found that participants had considerable difficulty in manoeuvring their hand from a starting position to a target position when their visual space had undergone a 90° rotation. Initially, their hand moved in an erratic fashion, generating highly variable zigzag-shaped trajectories, strongly suggestive of a biased random-walk process. After sufficient practice, movement time was significantly reduced, and the movements became less meandering, indicating that a certain amount of learning had taken place. However, the major drawback with these studies is their exclusive use of global performance measures (e.g. performance time, movement time and root-mean-square error), thereby leaving the finer spatio-temporal changes made during the course of each trial indiscernible. Although Cunningham and Vardi (1990) attempted to overcome the limitations of traditional measures by identifying and analysing various deterministic and curvilinear-shaped segments in partitioning of the movement trajectories, a later study suggested this approach was not particularly useful (Cunningham and Welch 1994). The diffuse control methodology, in contrast, provides a qualitatively different way of looking at learning because the analysis is based upon the properties of the segments that make up the zigzag trajectories of the hand.

Thus, the present study is an attempt to evaluate the validity of three within-trial measures of learning (detailed below) derived from the biased random walk/diffuse control models. The measures were adopted to explore the changes in hand movement trajectory during adaptation to the 90° visual rotation task. However, a direct application of the biased random-walk methodology to analysing movement control patterns is problematic, because movement trajectories consist of straight and curvilinear segments generated by variable velocities. To resolve this problem, movement trajectories were approximated as a sequence of straight-line segments (polygons). Individual segments of the polygon and the changes in direction from one segment to the next were identified in three different ways: (i) by sampling at a specific frequency to provide a temporal partitioning of the trajectory, (ii) by identifying large directional changes as corners and connecting them to approximate the spatial pattern of the trajectory, and (iii) by looking at local minimum values (valleys) of the velocity profile to produce a spatio-temporal partitioning. Although none of these methods provide a perfect trajectory approximation, each method is potentially useful in future studies depending on the specific aims of the research. Sampling the trajectory at every fifth point provides a strictly controlled temporal partitioning of the learners' movements and can potentially be used to relate our proposed measures to the popular Hurst coefficients which are also based on equidistant temporal sampling. This temporal sampling, however, does not capture the natural dynamics of individual runs or changes in direction. The second, spatial approximation method is sensitive to major directional changes and provides a good approximation of the trajectory's spatial properties, but is insensitive to stopping points that are not associated with directional changes, and it is hard to formalise. Also, this method tends to approximate a ballistic but curvilinear segment by a series of linear segments. The third, spatio-temporal method, in addition to identifying velocity minima associated with major changes in the movement trajectory, takes into account movements that appear to be in a straight line but actually reflect the adoption of a stop–start control strategy to which the spatial approximation is insensitive. The velocity partitioning is, on the other hand, insensitive to changes in direction that are unaccompanied by velocity changes (e.g. curvilinear movements) which the spatial approximation method isolates. Due to the methodological nature of the present study and the potential use of these techniques in future research, all three methods were utilised to evaluate specific properties of the trajectories.

The segments of the polygons have certain properties, such as length and direction (Berg and Brown 1972; Kadar and Virk 1998), which can be used as within-trial measures of the learning process. More precisely, the following properties – exemplified in Fig. 1 – were monitored:

A. Run length of each segment (RL).
B. Angle relative to the target for each segment (AT).
C. Drift (DR) or change in radial distance from the target.

Monitoring the changes of these variables over time was predicted to provide sensitive, within-trial measures of learning. These measures are expected to be superior to traditional measures of exploratory learning, because (a) a finer scale analysis of behavioural change is employed

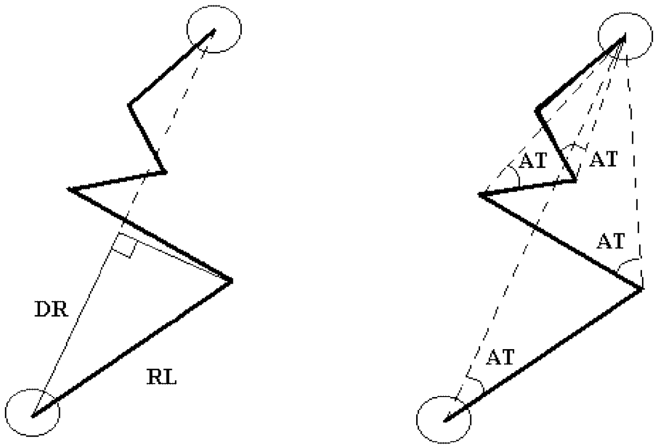

Fig. 1. Hypothetical biased random-walk trajectories, consisting of five segments connecting start and target positions. Each segment has a length (*RL*), drift (*DR*), and makes an angle with the target (*AT*)

and (b) the effect of using perceptual information in learning can be monitored. In addition to these new measures, performance was also measured using traditional global parameters [i.e. movement time (MT), trajectory length (TL), average velocity (AV), and peak velocity (PV)], thus allowing a comparison between the new analyses and existing findings based on traditional analyses.

2 Method

2.1 Participants

Five right-handed postgraduate students, one male and four female, participated in the experiment. Participants were naive to the task requirements and had normal or corrected-to-normal-vision.

2.2 Apparatus

Figure 2 depicts the experimental arrangement. All participants were seated at a table holding a stylus in their right hand. A curtain, placed directly in front of the learner, prevented vision of the arm. The stylus was 4 cm high and had a 5 cm square base to maintain the vertical orientation while it was moved by the learners across the surface of the table from a central target to peripheral targets placed 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° from vertical and at a distance of 15 cm. A reflective disc was mounted on the top of the stylus to allow movements to be tracked using a three-dimensional movement-analysis system (MacReflex system: two infrared cameras with a sampling frequency of 30 Hz). Recordings were made on a dedicated Power Macintosh G3 computer. A small camera, hidden from the participant's view to prevent prior knowledge of the visual rotation, was mounted above the table's surface to provide each participant with feedback. Feedback was presented on a TV monitor placed approximately 2 m from the participant. Presenting remote feedback that is rotated out of the plane of the movement is easy for the learner to accommodate and has minimal effects on learning (Cunningham and Welch 1994; Ghilardi et al. 1995; Goodbody and Wolpert 1999). The targets were white discs, 1.5 cm in diameter, placed on the surface of the TV monitor. In addition to a 90° anticlockwise rotation of the visually presented feedback, movements of 15 cm by the participant translated to a 9.5 cm movement on the screen creating further stimulus–response incompatibility. Thus, movements

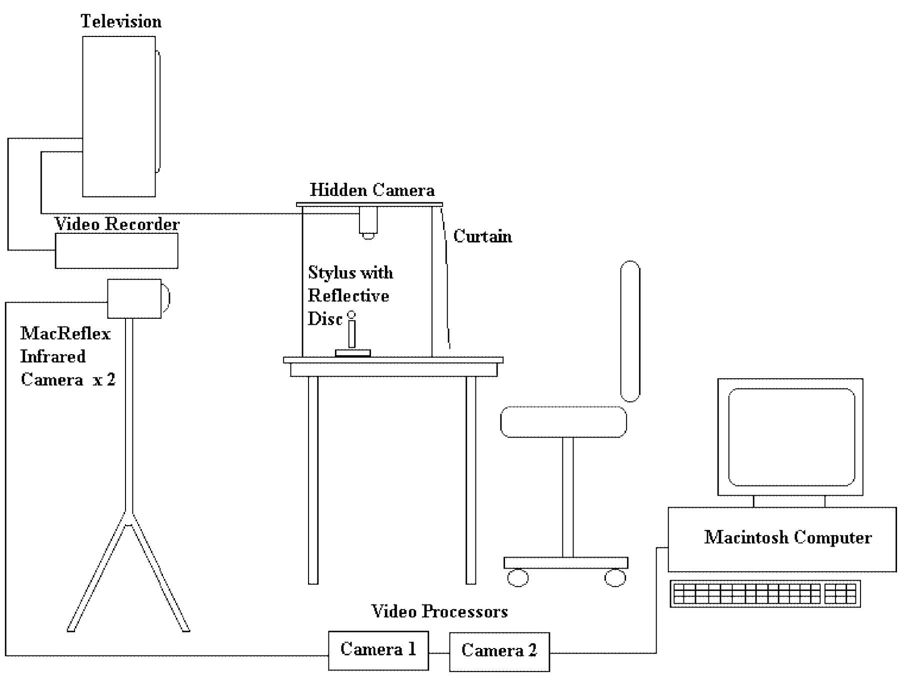

Fig. 2. Apparatus layout

made to the right appeared to move up the screen and movements toward or away from the body appeared to move right and left, respectively. All participants wore a black glove and low-contrast illumination was used to allow visual identification of the reflective disc mounted on the stylus but prevent visual feedback about the arm from the TV monitor.

2.3 Procedure

Participants were informed that they would be taking part in a learning experiment that involved moving a hand-held object from a central starting position to one of eight possible target locations and returning it to the starting position. They were told that they would not be able to see their hand or arm directly, but that feedback about the position of the hand would be provided on the TV monitor. They were unaware of the 90° visual rotation prior to commencing their first trial. Participants were required to perform five blocks of eight trials, consisting of a movement to each of the eight peripheral targets in a random order and a return movement to the central target. When moving to the target, participants were instructed to move quickly and not worry too much about accuracy. Upon reaching the target, participants were requested to pause for 2 s before returning to the central target (i.e. the starting position). This allowed subsequent partitioning of the series of movements into two trials. A new target was specified by the experimenter a few seconds after returning to the starting position. Participants were asked to make full use of the visual feedback provided on the monitor rather than trying to think about strategies in controlling their actions.

2.4 Analysis

Several custom-made computer programs were written and tested for calculating all the relevant parameters of the movement trajectories. Moving to a peripheral target and returning to the central starting position were treated as two separate trials. Since we were interested in only the ballistic segments of the movement, the individual trial profiles were then reduced by removing the final "homing phase", which is associated with a significant drop in velocity (below 10 mm s^{-1}) and short movements centred on the target (within 15 mm; Goodbody and Wolpert 1999). Typical examples of movement trajectories from trials early and late in the learning process with the homing phase removed can be seen in Fig. 3. Prior to the actual analysis, the movement trajectories of each trial were approximated as a sequence of straight-line segments (polygons). This was accomplished in three ways. The first method involved sampling every fifth data point to provide a temporal partitioning of each trajectory. The second method involved visually segmenting each trial run based on angular changes to the trajectory. The X–Y coordinates of the greatest angular deviation were recorded for each significant, visible change to the trajectory profile. This

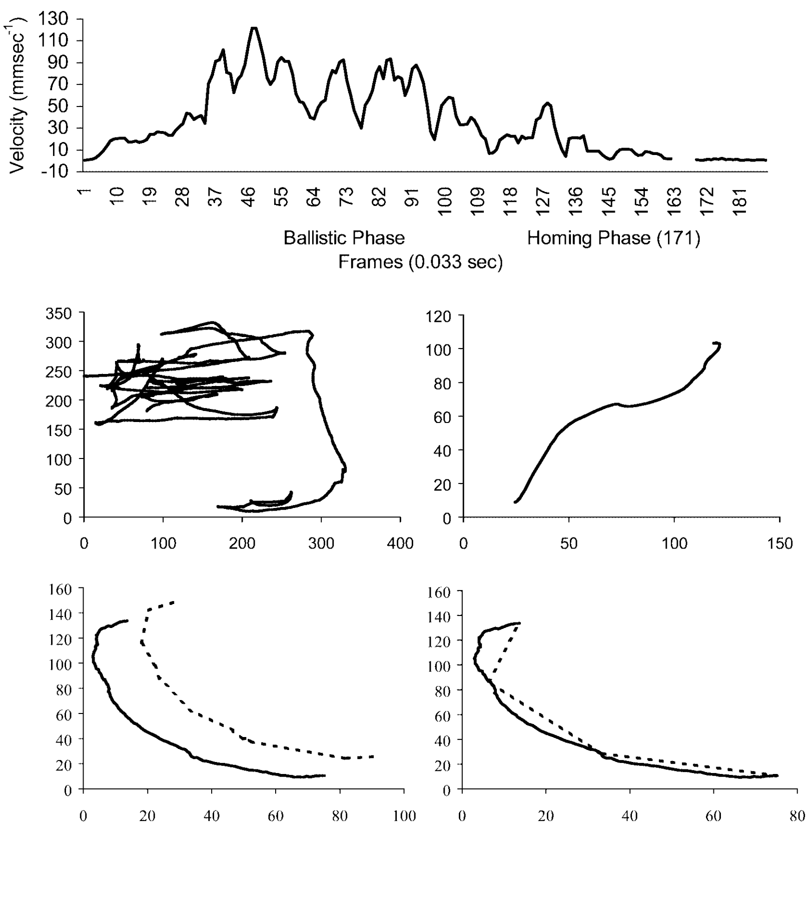

Fig. 3. The *top panel* illustrates the homing phase cut-off point (*right side*) for analysis of the ballistic phase of the movement. Typical movement trajectories from early and late trials (*middle left* and *middle right panels*, respectively) and a single movement trajectory, midway through learning, showing angle-partitioned segments (*lower left panel*; trajectory is shown transposed to the *right* for clarity) and velocity-partitioned segments (*lower right panel*)

partitioning method produced a spatial segmentation of the spatial deviations produced by the learner while attempting to reach the target.

The third partitioning method was based on the velocity changes that are associated with angular deviations in the movement trajectory. Changes in direction from one segment to the next were identified by local minimum velocity values ("valleys"). In each trial, valleys were defined in two ways: (i) as a minimum after a drop in the velocity profile below the mean velocity followed by an increase above the mean velocity, and (ii) by a significant drop in velocity of one or more standard deviations, followed by a similarly significant increase of velocity. Coordinates were generated corresponding to the minimum velocity within a single valley. Typical examples of the segmented trajectories can be seen in Fig. 3. For each segment the RL, AT and DR or change in radial distance from the target were measured (Fig. 1). In addition to these new measures, performance was examined using traditional global parameters (i.e. MT, TL, AV and PV). For ease of interpretation all analyses were performed on blocks of eight trials with the direction of the movement (*towards* the peripheral target or *returning* to the central target) as an additional within-subjects factor. Thus, a block × direction (5 × 2) analysis of variance (ANOVA) with repeated measures on both factors was performed taking each of the global and new within-trial measures' means as dependent variables. In some cases the assumption of sphericity was violated (Mauchley's test of sphericity), and so Greenhouse–Geisser's epsilon-adjusted probabilities are reported for all analyses. Although, changes in variability are often associated with learning, an analysis of the variability for the measures reported here revealed no obvious trends, except for MT which showed a gradual decrease in between-subject variability.

3 Results

3.1 Global outcome measures

The results of the repeated-measures ANOVAs with each of the four global measures as dependent variables can be seen in Table 1 (Mean, Standard error and 95% confidence intervals for each measure are given in Table 2.). It is apparent that the only global measure sensitive to a change over the blocks, and thereby suggesting that any learning had taken place, was MT. Multiple pairwise comparisons were calculated to isolate the effect of block. MT during block 1 was found to be significantly longer than during all other blocks except block 2; blocks 2 and 3 also had longer MTs than block 5. No other differences were apparent. In addition, the only measure to demonstrate an effect of direction was, again, MT. MT towards the peripheral targets was longer than MT towards the central target ($p < 0.05$). No significant interactions were found (Table 1). Mean values for each of the four global outcome measures from blocks 1 to 5 are illustrated in Fig. 4.

Table 1. Results of analysis of variance with repeated measures for all dependent variables

df		Block 4, 16	Direction 1, 4	Block × direction 4, 16
Traditional measures				
Movement time	*F*	8.06	14.79	2.08
	p	0.04	0.02	0.22
Average velocity	*F*	1.04	1.99	0.83
	p	0.38	0.23	0.47
Peak velocity	*F*	1.77	1.86	1.11
	p	0.25	0.24	0.37
Distance moved	*F*	3.21	4.95	1.72
	p	0.15	0.09	0.26
Temporally partitioned data				
Run length	*F*	1.67	1.63	1.12
	p	0.26	0.27	0.36
Angle to target	*F*	7.94	5.93	0.60
	p	0.03	0.07	0.57
Drift	*F*	4.27	4.44	0.34
	p	0.06	0.10	0.70
Spatially partitioned data				
Run length	*F*	10.52	2.90	0.78
	p	<0.01	0.16	0.46
Angle to target	*F*	14.39	11.01	0.11
	p	0.01	0.03	0.91
Drift	*F*	18.18	7.43	0.17
	p	<0.01	0.05	0.79
Velocity-partitioned data				
Run length	*F*	4.12	4.92	1.92
	p	0.02*	0.09	0.21
Angle to target	*F*	18.41	5.76	0.51
	p	<0.01	0.07	0.61
Drift	*F*	12.24	20.05	0.45
	p	<0.01	0.01	0.67

(*non-adjusted probability, Mauchley's test of sphericity non-significant)

3.2 Within-trial measures: temporally partitioned data

Three separate block × direction (5 × 2) ANOVAs with repeated measures on both factors was carried out with RL, AT and DR as the dependent measures. Only one significant effect was found (Table 1); specifically, AT decreased over the blocks (Fig. 5). Post-hoc comparisons (least-significant differences) revealed that AT was larger during block 1 than during all other blocks except block 5 ($p < 0.05$). It should be noted that DR was found to be marginally significant ($p = 0.06$).

3.3 Within-trial measures: spatially partitioned data

The results can be seen in Table 1. All four measures showed significant effects of the block. Specifically, RL was shorter during block 1 than during blocks 3–5, and RL for blocks 2 and 3 was shorter than for block 5, suggesting a gradual increase in RL over the entire learning period ($p < 0.05$). AT was greater during block 1 than during all other blocks, which did not differ from each other. Trials became less meandering over the learning period. There was also a gradual change evident for DR. During block 1, DR was shorter than

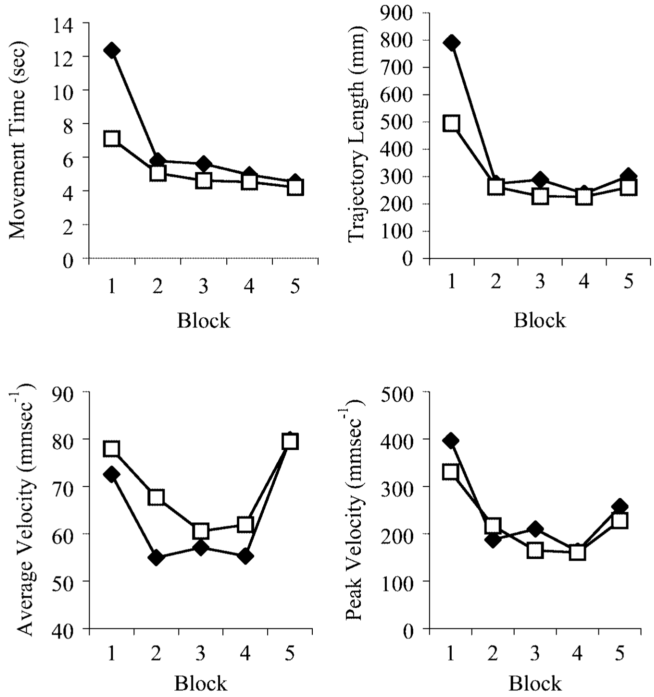

Fig. 4. Global outcome measures over blocks 1–5 (diamonds, movements to peripheral target; squares, return movements to central target)

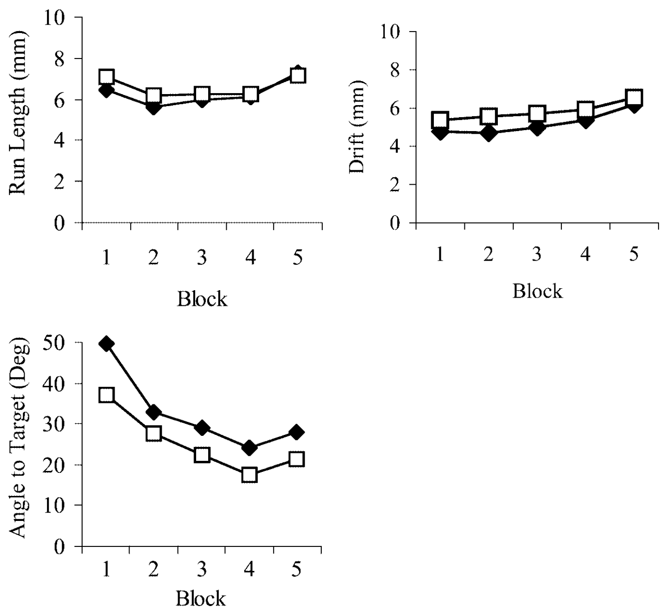

Fig. 5. Within-trial measures over blocks 1–5 for temporally partitioned segments (diamonds, movements to peripheral target; squares, return movements to central target)

during blocks 2–5; DR during block 2 was shorter than during blocks 4 and 5 and shorter during block 3 than during block 5 (all $p < 0.05$). In addition, a significant effect of direction was found for the AT measure, with mean AT greater in trials towards peripheral targets than in trials to the central target ($p < 0.05$). That is, the trials towards peripheral targets were more meandering than trials to the central target. The effect of direction for DR approached significance ($p = 0.053$), supporting the notion reported by all participants that movement to the central target was easier than that to the peripheral target. Mean values for each measure are illustrated in Fig. 6.

3.4 Within-trial measures: velocity partitioned data

The same analysis was replicated for the polygons generated by the velocity-based approximation. Again, significant effects of the block were found for all three measures (Table 1). A pattern of results similar to that found for the angle-partitioned data was found for the velocity-partitioned data. Pairwise multiple comparisons were utilised for closer examination of the block and direction effects ($\alpha = 0.05$ in all cases). RL was shorter in block 1 than during all other blocks, RL in block 2 was shorter than in blocks 4 and 5, and RL in block 3 was shorter than in block 5. This pattern of results is almost identical to that found using the angle partitioning method, and again indicates a gradual increase in RL during learning. AT was greater in block 1 than during all other blocks, consistent with the previous results. For the DR measure, significant differences were found between blocks 1, 3, 4 and 5, blocks 2, 4 and 5, and blocks 3 and 5. In all cases the earlier blocks displayed lower mean DR than the later blocks, as predicted. The effect of direction evidenced for the DR measure was a reflection of longer mean DR for trials towards the central target compared with trials towards the peripheral target. Mean values can be seen in Fig. 7.

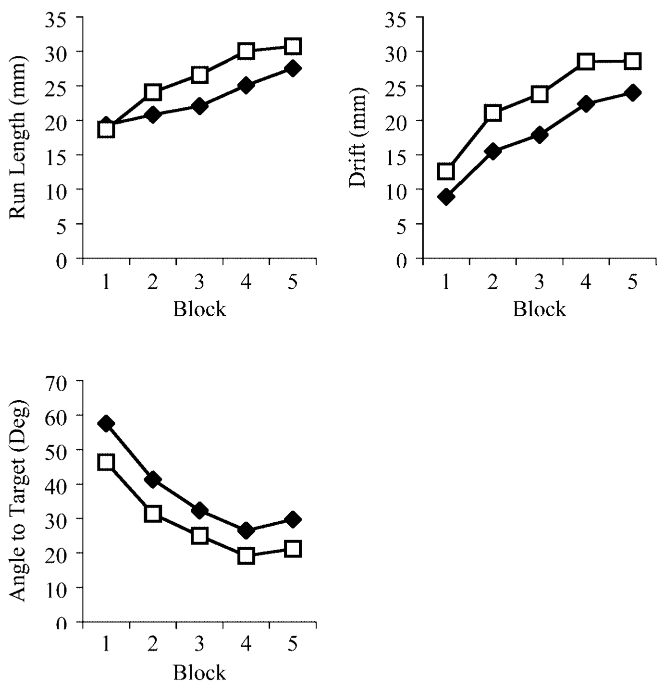

Fig. 6. Within-trial measures over blocks 1–5 for angle-partitioned segments (diamonds, movements to peripheral target; squares, return movements to central target)

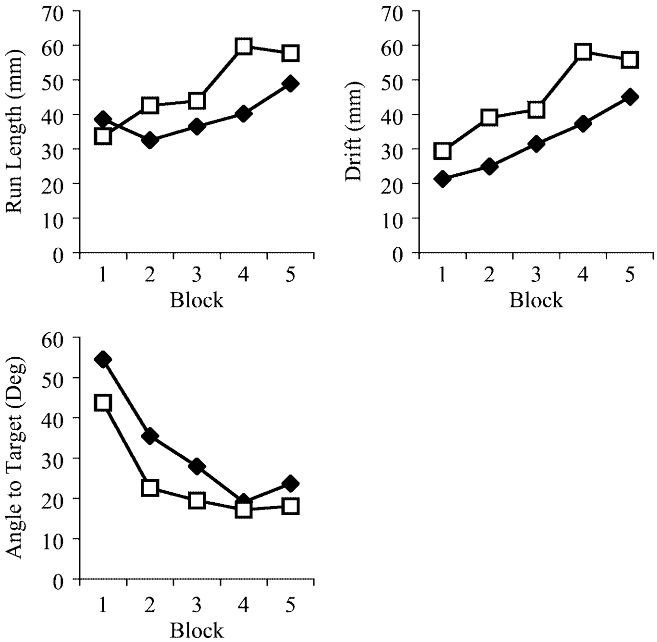

Fig. 7. Within-trial measures over blocks 1–5 for velocity-partitioned segments (diamonds, movements to peripheral target; squares, return movements to central target)

3.5 Distribution of runs during learning

Although the primary aim of this study was not a test of the diffuse control model itself, the proposed within-trial measures allow us to provide a simple statistical demonstration of the validity of the proposed model of exploratory learning. Thus, according to our postulated model of learning, the typical change in the meandering paths during learning would be due to a reduction in the role of randomness in movement production. We would thus expect runs to be distributed evenly across the available directions of movement during initial trials (reflecting a random distribution), but to be almost exclusively confined to the optimal direction of movement (reflecting a large target bias) in later trials. In all three partitioning methods, the number of runs for each of six possible AT categories was calculated for blocks 1 and 5, and are represented in Fig. 8. Runs are distributed more evenly during block 1 than during block 5. It is apparent that during block 1, runs were performed across the spectrum of possible directions. Nevertheless, Fig. 8 shows that individual runs were not evenly distributed; rather, they were biased towards the optimal direction of zero degrees from the beginning of learning. This observation provides preliminary support for the notion that random generation of movement paths may be playing a role in this process, but further analysis (e.g. of temporal correlation) is required before the role of randomness can be successfully described in a formal model.

4 Discussion

Accurate measurement is crucial for understanding the processes that underlie exploratory patterns in motor

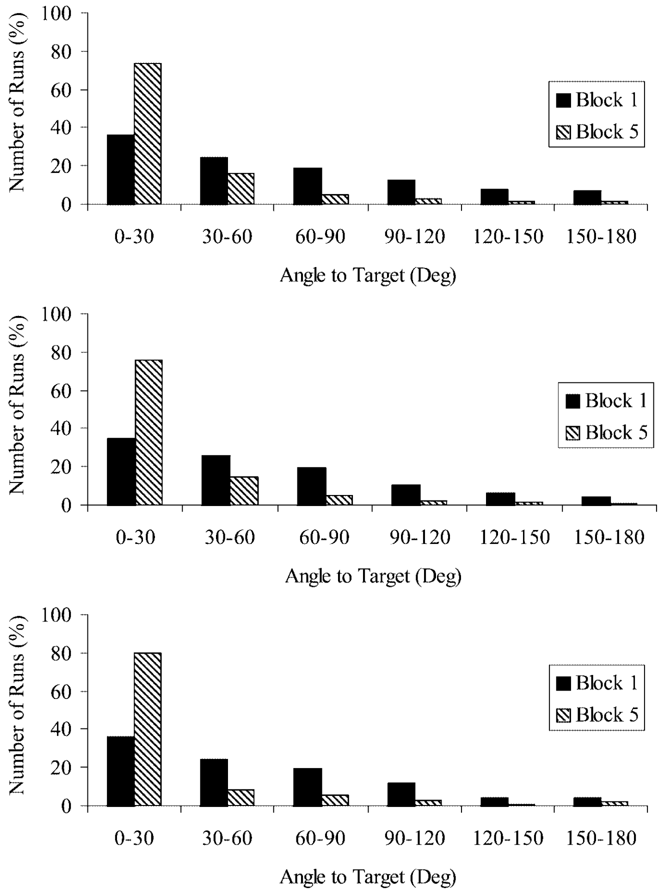

Fig. 8. Number of runs, represented as a percentage of the overall number of runs, occurring within each of six AT categories during blocks 1 and 5 (temporal partitioning, *upper panel*; spatial partitioning, *middle panel*; spatio-temporal partitioning, *lower panel*

learning. Accordingly, measures of learning should be sensitive to the changes that take place during skill acquisition, yet most studies have used trial-based global measures. They measure overall performance but do not actually measure the gradual *changes* taking place within trials. The present study attempted to remedy this shortcoming by analysing a visual adaptation task, adopted from Cunningham (1989), and comparing traditional trial-based measures of learning with new, within-trial measures.

Four traditional measures (i.e. MT, TL, AV and PV) were used to assess adaptation to a 90° anticlockwise rotation of the visual field. Of the four traditional measures, only one – MT (overall time taken to complete a trial) – was sensitive to gradual changes associated with learning.[1] This result replicates previous research that has demonstrated reductions in MT during

[1] The lack of effect for the other global measures is somewhat surprising. We have replicated the study with further 32 participants over various practice schedules and have found essentially similar results for both the global and within-trial measures. That is to say, our proposed within-trial measures and MT seem to be similarly effective measures of learning in this experimental design (based on blocks of eight trials).

Table 2. Mean, standard error, lower bound and upper bound 95% confidence intervals for all measures (in rows 1–4 for each measure, respectively)

	Block 1		**Block 2**		**Block 3**		**Block 4**		**Block 5**	
Traditional Measures	To Target	To Centre	To Target	To Centre	To Target	To Centre	To Target	To Centre	To Target	To Centre
Movement Time	12.35 2.87 4.38 20.32	7.09 1.52 2.88 11.29	5.77 .77 3.63 7.91	5.05 .81 2.80 7.30	5.60 .74 3.56 7.65	4.60 .44 3.37 5.84	4.95 .57 3.37 6.53	4.53 .63 2.79 6.27	4.53 .52 3.08 5.98	4.20 .55 2.66 5.74
Average Velocity	72.52 19.43 18.57 126.47	77.93 17.59 29.09 126.77	54.99 12.65 19.86 90.12	67.65 16.37 22.22 113.09	57.09 15.31 14.58 99.61	60.55 17.68 11.47 109.63	55.30 13.83 16.90 93.71	61.90 18.43 10.73 113.08	79.87 30.77 -5.56 165.29	79.45 29.67 -2.92 161.82
Peak Velocity	396.81 130.32 34.98 758.63	330.71 100.87 50.6 610.76	187.64 42.76 68.60 306.07	216.78 54.94 64.23 369.33	209.98 71.91 10.33 409.64	164.69 46.59 35.34 294.03	163.39 51.92 19.25 307.54	160.37 47.55 28.35 292.40	257.48 127.88 -97.6 612.5	227.48 76.78 14.19 440.53
Distance Moved	790.65 277.41 20.43 1560.9	494.83 175.77 6.82 982.85	274.53 29.49 192.64 356.4	262.89 33.62 169.54 356.25	288.10 48.68 152.93 423.27	227.66 25.59 156.59 298.73	237.34 36.98 134.67 340.02	225.75 28.27 147.27 304.23	302.35 87.99 58.03 546.67	261.36 43.92 139.42 383.30
Temporally Partitioned Data										
Run Length	6.43 1.29 2.83 10.04	7.06 1.11 3.96 10.16	5.63 .83 3.33 7.92	6.21 .86 3.83 8.59	5.98 1.01 3.18 8.77	6.25 1.0 3.47 9.03	6.08 1.07 3.11 9.05	6.28 1.08 3.27 9.29	7.27 1.65 2.68 11.85	7.12 1.51 2.93 11.30
Angle to Target	49.61 6.27 32.19 67.03	36.99 5.41 21.97 52.01	33.02 2.35 26.49 39.55	27.53 4.96 13.75 41.32	29.04 3.18 20.22 37.85	22.21 2.14 16.28 28.15	23.99 2.42 17.28 30.71	17.63 1.53 13.39 21.87	28.05 5.21 13.58 42.53	21.38 2.39 14.75 28.02
Drift	4.77 1.04 1.89 7.65	5.38 .84 3.06 7.71	4.70 .66 2.87 6.54	5.57 .79 3.37 7.78	4.99 .74 2.94 7.03	5.71 .98 2.99 8.43	5.36 .83 3.06 7.66	5.93 1.03 3.07 8.79	6.18 1.15 2.97 9.38	6.54 1.36 2.77 10.30
Spatially Partitioned Data										
Run Length	19.34 4.15 7.82 30.88	18.68 3.26 9.63 27.73	20.83 2.98 12.56 29.09	24.08 2.76 16.42 31.74	22.09 1.82 17.04 27.15	26.62 3.41 17.16 36.07	25.10 2.83 17.24 32.97	30.03 5.16 15.72 44.35	27.57 2.92 19.46 35.68	30.73 3.70 20.56 41.01
Angle to Target	118.05 7.14 98.23 137.86	120.76 7.90 98.82 142.69	129.33 4.92 115.69 142.98	129.92 12.07 96.39 163.44	135.70 8.49 112.14 159.27	136.97 7.73 115.50 158.43	139.56 7.35 119.13 159.99	149.70 2.53 142.69 156.72	137.14 7.35 116.72 157.56	138.56 11.89 105.53 171.60
Drift	8.94 1.79 3.95 13.92	12.59 2.58 5.42 19.76	15.49 2.22 9.32 21.67	21.08 2.73 13.52 28.65	17.92 1.95 12.51 23.34	23.78 2.99 15.48 32.09	22.40 3.03 13.99 30.81	28.51 4.97 14.73 42.29	24.03 3.83 13.38 34.67	28.59 3.16 19.81 37.37
Velocity (Spatio-temporal) Partitioned Data										
Run Length	38.61 7.69 17.23 59.98	33.63 4.64 20.76 46.50	32.52 3.10 23.91 41.14	42.54 2.45 35.74 49.35	36.46 3.57 26.56 46.36	43.92 5.15 29.62 58.23	40.17 4.66 27.23 53.11	59.71 6.65 41.25 78.16	48.94 7.56 27.97 69.92	57.71 7.64 36.51 78.91
Angle to Target	113.54 8.53 89.86 137.21	129.16 10.11 101.11 157.22	142.64 3.97 131.63 153.65	151.73 6.37 134.04 169.43	143.60 6.66 125.10 162.10	149.61 5.14 135.36 163.87	149.17 6.97 129.83 168.52	154.22 5.09 140.09 168.34	147.17 5.04 133.18 161.16	150.99 9.29 126.49 175.51
Drift	21.35 5.27 6.70 35.99	29.41 3.80 18.88 39.95	24.90 2.95 16.70 33.09	39.07 2.59 31.85 46.29	31.49 3.92 20.63 42.37	41.39 5.23 26.87 55.91	37.36 4.24 25.59 49.13	58.12 6.45 40.23 76.02	45.09 7.98 22.93 67.25	55.78 8.05 33.43 78.14

the course of adaptation to visual rotation (Cunningham 1989; Imamizu and Shimojo 1995). The MT was significantly longer for movement towards the peripheral targets than the return movement to the centre target, demonstrating that the return movements benefited from learning that occurred on the previous outward movement. This measure, however, provides no indication of the way in which participants adapted their movements to accomplish the task. For example, participants were asked to produce straight-line trajectories but their movement patterns were initially meandering. The apparent randomness in these patterns and the gradual change in producing less meandering trajectories are impossible to discern using the global measures. For this reason, finer measurement of the within-trial changes linked to learning is required to supplement the global measures.

The three within-trial measures – RL, DR and AT – , were designed to capture the decrease in meandering of the learner's movement trajectories. All three measures proved sensitive to the gradual emergence of straight trajectories from highly meandering trajectories that were characteristic of early attempts to complete the task. The changes in the three measures suggest that participants were able to learn the new mapping between their actions and the perceived outcome, and that this adaptation occurred gradually, throughout learning, rather than being isolated within the first block of trials as seems to be the case with all the global measures.

In addition to the validation of the new within-trial measures, three partitioning methods were used to reduce the trajectories to polygons. It appears that the first, temporal, partitioning method seems to be the least effective; it did not show the same sensitivity as the other two methods. Also, it fails to satisfactorily capture the dynamics of the movements produced whilst performing the task. Nevertheless, this partitioning strategy might be useful in future research because it can provide the basis for building a bridge to the currently popular fractional Brownian-motion analysis. The other two methods – spatial and velocity (spatio-temporal) based – seem to provide better approximation strategies. Both reveal the actual movements made by the performer and hence are more readily interpretable when assessing the control of motor actions. The spatial approximation method yielded similar results to the velocity method. Unfortunately, the use of this method might be problematic in future research because an appropriate algorithm for our manual strategy could not be defined, therefore the velocity-based partitioning would be preferable as the primary method of choice in future applications of these measures.

These findings represent a step forward in the measurement of exploratory motor learning. Two levels of analysis were used and positive results were found for both. On a global level, the time taken to complete each trial was sensitive to changes associated with learning and direction of movement. Although MT is a sensitive global measure, it is clearly insufficient to describe exploratory learning. Exploratory learning is more than just a reduction in time taken to complete the task. The proposed within-trial measures appear to be valid candidates for this role because they capture the essence of the learning process. Participants were able to make perceptually guided movements that brought them successively closer to the target. The DR measure, derived from the RL and the direction of the run in relation to the target (AT), provides a measure of task success (i.e. getting closer to the target) independently of whether the learner's hand is moving directly towards the target or in a direction that reduces the distance between the hand and the target. The movement trajectory can be altered in response to decreasing or negative DR (moving towards the target at a successively slower rate or moving away from the target, respectively) rather than a planned alteration based on predicted position, current direction and distance moved. Since the bias in directional changes and RL can be captured by DR, it might be appropriate to categorise the underlying learning process as a diffuse control strategy with increasing DR. For this reason, the DR measure is currently being utilised by the authors to develop a detailed model of exploratory learning based on the concept of diffuse control.

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