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Dynamics of Movement Patterning in Learning a Discrete Multiarticular Action

Jia Yi Chow, Keith Davids, Chris Button, and Robert Rein

From a nonlinear dynamics perspective, presence of movement variability before a change in preferred movement patterns is hypothesized to afford the necessary adaptability and flexibility for seeking novel functional behaviors. In this study, four novice participants practiced a discrete multiarticular movement for 12 sessions over 4 weeks. Cluster analysis procedures revealed how changes between preferred movement patterns were affected with and without the presence of variability in movement clusters before a defined change. Performance improved in all participants as a function of practice. Participants typically showed evidence of change between preferred movement clusters and higher variability in the use of movement clusters within a session. However, increasing variability in movement clusters was not always accompanied by transition from one preferred movement cluster to another. In summary, it was observed that intentional and informational constraints play an important role in influencing the specific pathway of change for individual learners as they search for new preferred movement patterns.

Keywords: learning, transitions, movement variability, cluster analysis, informational constraints

The question of how neurobiological systems successfully acquire movement skills has been studied from a number of theoretical perspectives including nonlinear dynamics, a theory particularly suited to the study of neuro-behavioral transitions (Newell, Liu, & Mayer-Kress, 2001). From this viewpoint, motor learning has been characterized as a process of change between stable movement patterns (e.g., Liu, Mayer-Kress, & Newell, 2003, 2006; Schöner, Zanone, & Kelso, 1992). A central tenet in nonlinear dynamics posits that dynamical structures of control spread across several levels of analysis and their functioning in neurobiological systems is bound by self-organization under constraints (Kauffmann, 1995). Patterns of behavior can spontaneously emerge as a consequence of the constraints present in specific learning contexts (Schmidt & Fitzpatrick, 1996).

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Studies in nonlinear dynamics have suggested that over time, learning can be characterized as the evolution of a potential landscape describing the destabilization of previously preferred movement solutions in neurobiological systems for a “to-be learned” coordination pattern (Thelen, 1995). The acquisition of coordination is viewed as a process of searching for appropriate *attractors*, preferred functional coordination patterns, into which a neurobiological system can settle during a task or activity (Liu et al., 2006). Consequently, motor learning can be characterized by nonlinearities under constraints in which transitions (including sudden jumps and regressions) between preferred movement patterns may be observed over different time scales (see Liu et al., 2006; Newell et al., 2001). Moreover, it has been further suggested that variability in movement typically accompanies pattern changes during motor learning in continuous cyclical tasks (e.g., Vereijken, Van Emmerik, Bongardt, Beek, & Newell, 1997, in a slalom-like movement task; Zanone & Kelso, 1997, in a bimanual finger coordination task). However, are critical fluctuations in movement variability a necessary prerequisite of transitions while learning a discrete multiarticular task?

Most studies of the dynamics of motor learning have tended to favor models of bimanual finger coordination (e.g., Schöner et al., 1992) or continuous movements (e.g., Ko, Challis, & Newell, 2003; Nourrit, Delignieres, Caillou, Deschamps, & Lauriot, 2003; Vereijken et al., 1997). In this study we investigated the learning of discrete multiarticular actions. Although Southard (2002, 2006) previously investigated changes in movement patterns in a discrete throwing task, the emphasis was on manipulating parameters, as well as instructions, in affecting a change in throwing patterns. Few studies in nonlinear dynamics have attempted to examine the process of change and the presence of transitions between preferred coordination patterns in a discrete multiarticular action over extended practice periods.

Discrete movements can provide useful models to investigate the process of change in coordination between distinct trials and practice sessions because they differ from continuous movements in important ways. One critical difference concerns the specificity of the constraints in many continuous and discrete tasks. In many discrete movements, like interceptive actions, positional accuracy in termination of the end point is most important in achieving the final goal (Guiard, 1997). Task constraints differ considerably when one is learning to move a limb to a specific spatial location and timing the intended contact of an effector with an object, compared with when one is continuously waving an arm or wagging a finger. Schöner (1990) previously modeled differences between discrete and rhythmical movements, suggesting that the influence of each individual's intentionality is a unique source of behavioral information stabilizing action pattern dynamics. He showed how performance of a discrete movement could, in principle, be stabilized or perturbed by the intentions of the performer.

Research on discrete movements is theoretically significant because it can provide a window on the interface of cognition and action during motor learning (see Summers, 1998). Between trials when learning discrete movements, more time and opportunity is available for learners to evaluate behavioral information that could impact the process of change between preferred movement patterns. The impact of intentions and behavioral information such as information from the environment or experience from previous trials and sessions can be examined in detail. Schöner's (1990) modeling led us to expect a great amount of interindividual variability during

the performance of discrete multiarticular actions. The assumption is that because individuals' intentions differ based on perceived physical competency to achieve the task goal (although the general intention to complete the task could be similar), so will the movement patterns produced during motor learning.

Questions arise over the existence of key hallmarks of change between preferred movement patterns when learning a multiarticular discrete action. For example, currently, it is not known whether nonlinear transitions between preferred movement patterns may occur in a similar fashion as observed in previous studies of bimanual finger coordination. As a function of varying individual constraints, do we expect to see each learner showing distinct preferred movement patterns during the course of learning a skill? As well as pattern transitions, another important hallmark feature of learning in nonlinear dynamics to look out for is the presence of critical fluctuations or high levels of movement pattern variability immediately before a change in preferred movement patterns. Critical fluctuations have been observed in bimanual finger coordination studies and occur readily before a change in stable patterns (either to in-phase or antiphase). Critical fluctuations or high movement variability are vital in providing neurobiological systems with the requisite adaptability and flexibility for exploring novel coordination solutions (Riley & Turvey, 2002). It is not known if high levels of movement variability might be observed during the acquisition of discrete multiarticular actions during a prolonged period of practice. Therefore, high levels of movement variability were used in this study to interpret the presence of critical fluctuations as outlined in dynamical systems theory. Movement variability was considered important in studying adaptive changes in behavior during learning because a cluster analysis technique was used to identify movement patterns used by participants within distinct practice sessions. High levels of variability in movement clusters were regarded as a better reflection of the macro variability that might exist in the use of movement clusters by learners in this study because we are looking at a different timescale (i.e., learning) from that in which critical fluctuations were originally shown (i.e., motor control). Furthermore, understanding stability in dynamical movement systems entails examining concepts such as *critical slowing down* as a consequence of a perturbation intervention. However, for this study, the term *preferred* was used instead of *stable* to acknowledge that the stability of a movement cluster was not determined, but rather movement clusters were categorized as being *preferred* by participants if the use of the movement clusters satisfied certain a priori criteria.

The current study investigated individual transitions between preferred states of motor system organization during practice of a discrete multiarticular action. For this purpose, we studied the process of change in movement patterning of a lower limb interceptive action for kicking a ball. During practice, we examined movement variability and its effects on the nature of transitions from one preferred movement pattern to another novel preferred pattern. A small sample size of four participants was selected to allow an in-depth investigation of the processes underlying movement variability changes and transitions between preferred movement patterns, negating some of the previously acknowledged problems with averaging data across different individuals in group-based analyses (see Stergiou, 2004). The use of such multiple-baseline, single-participant analyses in examining human movement behavior can also provide a suitable methodological framework for understanding movement pattern changes as a function of practice. For these

reasons many recent studies have adopted such a research design (e.g., Chen, Liu, Mayer-Kress, & Newell, 2005, in learning a pedalo locomotion task; Haibach, Daniels, & Newell, 2004, in learning cascade juggling; Hodges, Hayes, Horn, & Williams, 2005, in learning a soccer kicking task; Hong & Newell, 2006, in learning a skiing task).

The aim of this study was to investigate learning of a discrete multiarticular action by identifying the presence of change between preferred movement patterns derived from relevant kinematic variables with cluster analysis procedures during the acquisition process. It is expected that participants will demonstrate different preferred movement patterns during the learning phase of the study. In addition, we seek to establish whether levels of variability in movement patterns increased before a change in preferred movement patterning. We predict that there will be increased levels of variability in movement patterns before a transition between preferred movement patterns.

Methods

Participants

Four male novice participants (age 27.3 ± 4.03 years) were recruited for this study. All had no competitive playing experience in ball games involving lower-limb interceptive actions, such as soccer, at any level. Voluntary and informed consent were obtained from all participants, and procedures employed in the study were in accordance with the participating institution's ethical guidelines.

Task and Apparatus

In the experimental task, all participants were asked to kick a soccer ball (a FIFA-approved size 5 ball; mass = 420 g; circumference = 68cm) over a barrier to a skilled receiver with their dominant foot. No explicit verbal or visual instructions were provided on how to kick the ball over the barrier. Participants were simply informed that the task goal was to kick the ball over the height barrier to land at the feet of a receiving individual or within a landing zone in front of the receiver with appropriate force control to allow easy control of the ball by the receiver. Video film capturing ball flight only onto the receiver's feet was shown to ensure understanding of the task goal. The novice participants learned the task on a 2×2 m area of a synthetic surface in a laboratory. Target positions were located on a field outside the laboratory, with the player kicking the ball onto the field for all trials. A horizontal bar (length = 4 m) supported by two adjustable vertical poles (2 m each) provided the height barrier for the task. Colored bands (approximately 0.5 m) attached to the horizontal bar were used to simulate a perceptual barrier without occluding the receiver's view of the participant. All participants were required to kick to seven different target positions located between 10 m and 14 m perpendicular to the kicking position and with bar height manipulated between 1.50 m and 1.70 m from the ground. However, for the practice target positions (i.e., T1, T2, T3, and T4), the bar height was kept at 1.6 m (see Figure 1 for detailed information about the setup).

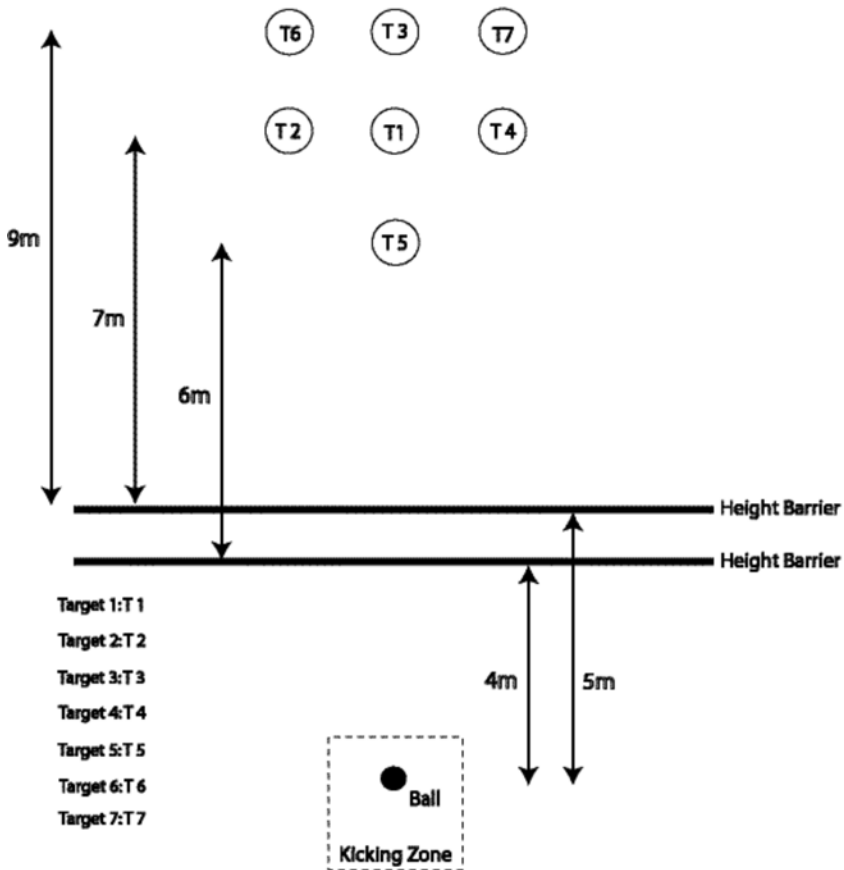


Figure 1 — Schematic representation of task set up to all target positions. Target T1: bar height (1.6 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T1 (12 m); Target T2: bar height (1.6 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T2 (12 m); Target T3: bar height (1.6 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T3 (14 m); Target T4: bar height (1.6 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T4 (12 m); Target T5: bar height (1.5 m), perpendicular distance of ball to bar (4 m), and perpendicular distance of ball to T1 (10 m); Target T6: bar height (1.6 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T1 (14 m); Target T7: bar height (1.7 m), perpendicular distance of ball to bar (5 m), and perpendicular distance of ball to T1 (14 m).

In the kicking task, all participants wore soccer indoor shoes and shorts for all test and practice sessions. Kinematic data were captured by six infrared cameras (ProReflex, Model MCU 1000). The cameras were connected to the Qualysis On-line Motion Analysis system (Gothenburg, Sweden), and data were recorded at 240

Hz. Twenty-nine spherical reflective passive markers were placed on key anatomical points. Surface markers were placed on the following anatomical landmarks: sphenoid, mandible, acromion process, lateral epicondyle (elbow), lateral point on the radial styloid and medial point on the ulnar styloid, superior iliac crest, greater trochanter, lateral epicondyle (knee), medial epicondyle (knee), lateral malleolus, medial malleolus, first metatarsal head (only for nonkicking foot), and fifth metatarsal head. Three-dimensional Euler joint angles of flexion and extension were derived for the hip, knee, ankle, pelvis, and trunk from the respective segments as defined by the marker sets, but only the angle in the primary plane of motion was used for further analysis. A 20-m measuring tape was used to determine distance between the landing position of the ball on the field (when the ball did not contact the receiver) and the respective target position. Ball landing position for each trial was established visually and marked by two research assistants with one end of the measuring tape. All measurements were taken by three research assistants who were trained and supervised for 2 weeks as part of the pilot phase of the study to ensure measurement reliability.

Procedures

Pre- and Posttest Sessions. Participants performed 5 habituation trials by kicking the ball out to the field without any requirement for satisfying constraints of height clearance or target accuracy. Thereafter, all participants performed 10 trials kicking to T1. Subsequently, participants performed another 5 trials each to T5, T6, and T7 in a randomized order, completing a total of 25 test trials for the pre- and posttest sessions. The 10 trials to T1 enabled us to determine the coordination of the kicking action, and the 15 trials to T5, T6, and T7 were used to identify whether novices could vary kicking foot speed to achieve the task goal under the different height and distance constraints (see also Chow, Davids, Button, & Koh, 2006). Participants were allowed to rest as needed between trials, with intervals ranging between 10 and 30 s in duration. Each test session took between 45 and 60 min to complete. Pre- and posttest sessions were separated by a 4-week practice phase.

Practice Sessions. Participants performed the warm-up routine as in other sessions before practicing 10 kicking trials each to T1, T2, T3, and T4 (a total of 40 trials per session) in a randomized order. The requirement for participants to perform 40 trials was based on pilot work that was undertaken to verify an adequate number of trials within each session to observe possible changes in movement clusters, without incurring the negative effects of fatigue on participants during the practice. T1, T2, T3, and T4 did not differ greatly in relation to target distances, and bar height was also kept at 1.6 m for all the practice positions. These slight variations in target locations (see Figure 1) allowed us to observe how each participant explored their individual perceptual-motor workspaces to support their learning (see Newell, Liu, & Mayer-Kress, 2003). It was decided not to greatly vary the location of targets in terms of positional and height constraints so that the use of multiple, randomly ordered target positions would not have an inordinate impact on switches between specific movement clusters and to keep learners motivated in the kicking task. All novice participants underwent a 4-week practice phase with 3 sessions per week (a total of 12 sessions). A rest interval of 2 to 3 days between sessions conformed to

the recommendations of the benefits of a distributed practice schedule (see Magill, 2007). In addition, they were required to perform an additional 15 kicking trials to T5, T6, and T7 (5 trials to each position) in a randomized order at every second session (i.e., at the 2nd, 4th, 6th, 8th, 10th, and 12th practice session; see Chow et al., 2006). In total, all participants performed 570 trials during the practice phase. Rest intervals between trials were similar to the pre- and posttest sessions, and each practice session took between 60 and 90 min to complete.

Data Analysis

Performance Outcomes. Performance of the kicking task was assessed by how accurately and effectively weighted the chipped passes were to the receiver's feet. Outcome scores were determined from a 7-point Likert rating scale, with emphasis on accuracy and ease of ball reception (see Table 1). For example, if the ball crossed the height barrier successfully and landed within 0.6 m from the receiver's feet, a score of 7 was recorded. A measurement tape was used to determine the horizontal displacement between the landing position of the ball and the respective target position. All measurements were taken by the three research assistants, who were trained and supervised for 2 weeks as part of the pilot phase of the study to ensure measurement reliability. The scale was devised by the researcher and validated by two certified coaches from the Asian Football Confederation. Validity of the rating scale was verified in a series of pilot studies conducted on groups of skilled and novice participants to examine performance scores. To determine interscorer reliability between the experimenter and the certified coaches, a sample of 25 trials was captured on video film and presented to two certified coaches for scoring. Interscorer reliability between the experimenter and each coach was 100% and 96%, respectively. The performance rating scale allowed the magnitude of error from the task goal to be determined for all trials because some kicks might have inadvertently contacted the receiver's body, preventing error distance from being recorded. Means and *SDs* of individual participants' performance outcome scores are presented only for trials selected for kinematic analysis.

Joint Range of Motion. Kinematic variables provided information about the specific spatio-temporal patterning of the kicking coordination modes of all participants. Time-continuous joint-angle data for the hip, knee, and ankle for the kicking and nonkicking limbs, as well as trunk (angle between pelvis and thorax segments) and trunk lean (angle between the thorax segment and the horizontal plane; in degrees), for each individual trial were collected for the duration of the limb-movement sequence beginning from the instant of initiation of knee flexion (before ball contact) to the end of peak hip flexion (after ball contact) of the kicking limb (see Chow et al., 2006). After visual inspection, data were filtered using a low-pass Butterworth digital filter with the Visual 3D software at frequency 7Hz. All trials were normalized to 100 data points between the start event (initiation of knee flexion) and end event (peak hip flexion), with movement time normalized to allow for simultaneous comparison across individuals and trials.

Analytical techniques to examine timing relationships (e.g., time lags) and relationships between joint motions (e.g., cross-correlation ratio analysis), as previously described by Temprado, Della-Graa, Farrell, and Laurent (1997) in their

**Table 1 Performance Rating Scale for Soccer Kicking Task
Emphasizing Weighting and Accuracy of Passes**

Points/ Score	Description
7	<ul style="list-style-type: none">• Ball played to feet (below knee) or within landing zone in front of receiver (0 m to 0.6 m) and appropriately weighted for ease of control
6	<ul style="list-style-type: none">• Ball played to the thighs (between the knee and the abdomen) and appropriately weighted for ease of control• Ball played to feet (below knee) or landing zone but not weighted for ease of control• Ball played to the sides of the receiver at any level below the head (which challenges the receiver to move one step to control the pass) and the ball lands within 1.0 m from the receiver but outside of landing zone (0.61 m to 1.0 m)
5	<ul style="list-style-type: none">• Ball played to chest (above the abdomen) and appropriately weighted for ease of control• Ball played to the thighs (between the knee and the abdomen) but not appropriately weighted for ease of control• Ball played to the sides of the receiver at any level below the head (which challenges the receiver to move one step to control the pass) and the ball lands between 1.01 m and 1.5 m from the receiver
4	<ul style="list-style-type: none">• Ball played to the head• Ball played to chest (above the abdomen) but not appropriately weighted for ease of control• Ball played to the sides of the receiver at any level below the head (which challenges the receiver to move one step to control the pass) and the ball lands between 1.51 m and 2.0 m from the receiver
3	<ul style="list-style-type: none">• Ball lands between 2.01 m and 2.5 m from the receiver
2	<ul style="list-style-type: none">• Ball lands between 2.51 m and 3.0 m from the receiver
1	<ul style="list-style-type: none">• Ball lands more than 3.0 m from the receiver• Ball fails to cross the net barrier or touches the net barrier before reaching the receiver

Note. Scoring was not dependent on how well the live receiver controls the ball. The presence of a live receiver is to provide a more ecologically valid representation in terms of target attainment for the kicker.

study on volleyball serves, were actually adapted for the same participants in Chow, Davids, Button, and Koh (2008) to investigate coordination changes. The focus for this study was to specifically identify differences between participants’ movement patterns, and cluster analysis procedures with time-continuous joint-angle data as input variables still provided an ideal approach to achieve this aim.

All trials for the pre- and posttest sessions were analyzed. However, because of the large number of observations, only selected practice trials were chosen for analysis within each practice session. Specifically, 18 trials per session were analyzed for kicks to T1, T2, T3, and T4. Table 2 shows the distribution of the selected trials that were analyzed.

Table 2 Distribution of Selected Trials Analyzed for Practice Sessions to Positions T1, T2, T3, and T4

	Phases of practice session	Trials
1	Early	2nd, 4th, 6th, 8th, 10th, 12th
2	Middle	15th, 17th, 20th, 23rd, 25th, 27th
3	Late	29th, 31st, 33rd, 35th, 37th, 39th

Cluster Analysis and Validation. Following the methods used by Schöllhorn (1998) and Jaitner, Mendoza, and Schöllhorn (2001), a cluster analysis approach was used to determine preferred movement patterning. Hip, knee, and ankle-joint range-of-motion data for kicking and nonkicking limbs, as well as trunk and trunk-lean angles, were selected as input variables during the preprocessing stage because these eight variables have been observed to be the most relevant in describing the kicking movement. Based on previous work (e.g., Lees & Nolan, 2002), it was expected that differences between kicking patterns would emerge by comparing these selected variables. The angles were time normalized, and a matrix for each trial was obtained (see Jaitner et al., 2001). Differences between trials were calculated using the Euclidean distance. The AGNES clustering algorithm in R software (version 2.31) was used to construct a tree-like (dendrogram) *hierarchy* of clusterings of k clusters (where the most suitable value of k is subsequently validated through cluster validation techniques). A dissimilarity measurement was constructed with the DAISY function in the R software in which the dissimilarity between clusters was calculated using the “average” linkage method (see Kaufman & Rousseeuw, 1990).

The clustering distribution presented was validated using the multiscale bootstrap resampling procedure developed by Shimodaira (2002, 2004) in the R software (pvcust R package). This method is applicable to a large class of clustering problems including hierarchical clustering (Suzuki & Shimodaira, 2004), providing an indication of how strongly a cluster is supported by the data set. Accuracy of the probability of *valid* clustering was measured with alpha values ranging from 0 to 1. For example, if the alpha value of a cluster was recorded as $p = .90$, it would indicate that there was a 10% chance that the clustering of data under the particular cluster occurred because of chance. The convergence of the bootstrapping procedure was assessed investigating the standard errors of the p values. Furthermore, the Hubert- Γ statistic, which gives an indication of the partitioning that best fits a given data set (Halkidi, Batistakis, & Vazirgiannis, 2002), was used to validate the cluster results. The Hubert- Γ coefficient has been shown to be simple, precise, and robust (see Zhao, Liang, & Hu, 2006) and was used to determine the optimal number of clusters.

Even though it is the objective of the cluster analysis procedure to identify different movement patterns from the observed movement clusters, it is possible that different scaled movement patterns could be categorized as different movement clusters. In this study, however, different scaled movement patterns could still be important to identify because slight differences in kinetic (e.g., force exerted) or kinematic (e.g., joint range of motion) input into the kicking action can result in vastly different performance outcomes. So, in complex multiarticular movements

such as the kicking action, scaled movements can still be characterized as quite distinct from one another and can be considered to be a distinct preferred movement cluster.

Cluster Movement Switch Ratio (SR). Cluster movement switch ratio (SR) provides an index on the preferability of movement patterns and is defined as the number of switches divided by the maximal possible number of switches within a practice session (adapted from Wimmers, Savelsbergh, Beek, & Hopkins, 1998). A switch can occur between any two neighboring trials. For example, in a series of three trials, the maximum number of switches would be two. An additional point to note, consider two hypothetical practice sessions in which two movement clusters (C1 and C2) are used. In the first session, for the following sequence, C1C1C1C1C2C2C2C2, the SR would be 1:7 (or 0.143). In contrast, for the second session C1C2C1C2C1C2C1C2, the SR would be 7:7 (or 1) even though the probability of occurrence is 50% in both sessions. It should be noted that the SR is a ratio measure of the variability of the transitions between movement patterns and is not the variability of a given movement pattern before transition. Nevertheless, the SR provides an index to highlight the global movement variability in the neurobiological system through the amount of different movement pattern variability exhibited by individual participants.

Criteria for Transitions Between Preferred Movement Clusters. Following Wimmers et al. (1998), we imposed the following criteria as evidence of a transition between movement clusters. A transition from one cluster of movement (e.g., C1) to another cluster of movement (e.g., C2) was deemed to be present when both clusters occurred in at least 14 out of 18 (78%) trials in their respective sessions. In addition, a switch ratio (SR) of not more than 0.235 (4:17) has to be present for those 18 trials within their respective session for a cluster to be considered as a *preferred* movement cluster in that session. Thus, $SR \leq 0.235$ with $\geq 78\%$ occurrence for a particular cluster will have to be observed for it to be categorized as a *preferred* movement cluster. An increasing switch ratio signals increasing variability in movement clusters within a session (Wimmers et al., 1998). Similarly, a low or decreasing switch ratio denotes decreasing variability in movement clusters in a session.

Results

Performance Outcomes

Performance scores to T1, T2, T3, and T4 were measured for 18 trials per session. Although the practice data were noisy, all participants demonstrated a general increasing trend in performance scores from practice session 1 to session 12 (see Figure 2). There were significant improvements between pre- and posttest performance scores for all participants ($p \leq .05$).

Cluster Analysis and Cluster Movement Switch Ratios

Cluster analysis was performed on the practice trials for each individual participant, and an intraindividual analysis was undertaken to examine changes in movement

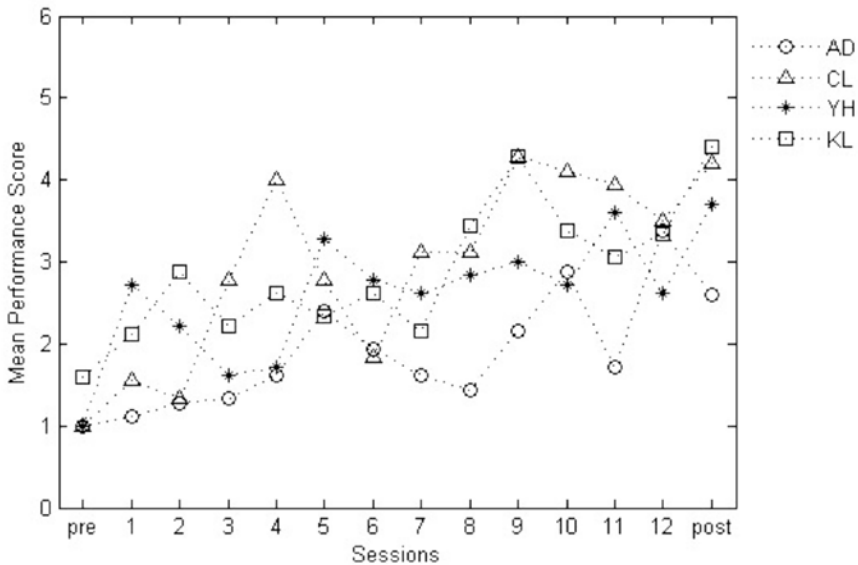


Figure 2 — Performance scores for individual participants for all practice sessions. Participant AD: pre (1.0 ± 0), post (2.6 ± 2.07); Participant CL: pre (1.0 ± 0), post (4.3 ± 1.81); Participant YH: pre (1.0 ± 0), post (3.7 ± 2.31); Participant KL: pre (1.6 ± 1.26), post (4.4 ± 2.01).

clusters as a function of practice. Later we examine how each participant adapted movement patterns during the extended practice period.

Participant YH

The Hubert- Γ index indicated that the most suitable number of clusters in the movement patterns observed by YH during practice was 7 (with the highest index of 0.6005). However, from the multiscale bootstrap resampling procedure (Shimodaira, 2002, 2004), when 7 clusters were included in the dendrogram, cluster 7 exhibited an alpha value of only .58. When 6 clusters were constructed, the alpha value rose to .74 and above (see Figure 3). Consequently, a 6-cluster dendrogram was constructed because it provided a more accurate clustering representation of the data set based on the multiscale bootstrap procedure (see Figure 4).

To highlight differences between movement clusters, clusters 1 and 2 (which were some of the major clusters of trials for YH, comprising 12% and 68% of all trials analyzed, respectively) were compared. Means for individual kinematic variables were determined for all trials within the respective group of clusters and plotted to ascertain differences (see Figure 5). It must be stressed that the selection of only two movement clusters (clusters 1 and 2) for participant YH is for presentation purposes only to highlight that the cluster analysis procedure was able to appropriately identify differences between movement clusters. However, the importance and

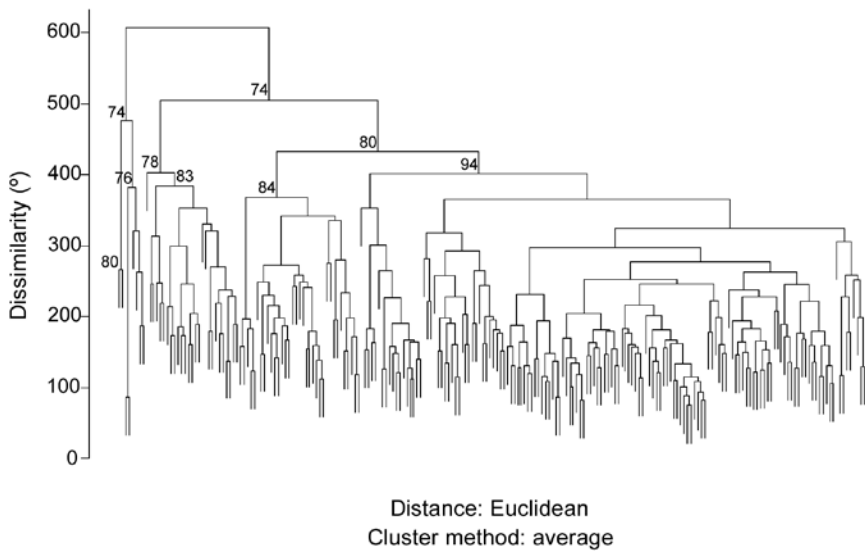


Figure 3 — Multiscale bootstrap resampling for Participant YH. Numbers represent the p values for the cluster of trials under the respective branch in the hierarchical dendrogram.

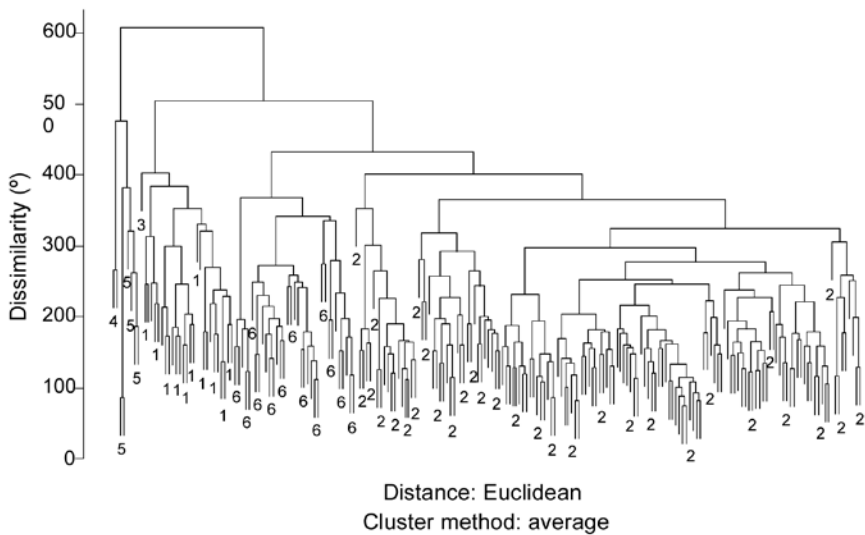


Figure 4 — Dendrogram with cluster partition for Participant YH. Numbers represent clusters.

relevance of other movement clusters as demonstrated by participant YH should not be downplayed. Figure 5 provides the visual qualitative discrepancy between movement clusters evident in the performance of participant YH.

Figure 6 shows the distribution of movement clusters for individual trials as a function of practice sessions for participant YH. It can be observed that participant

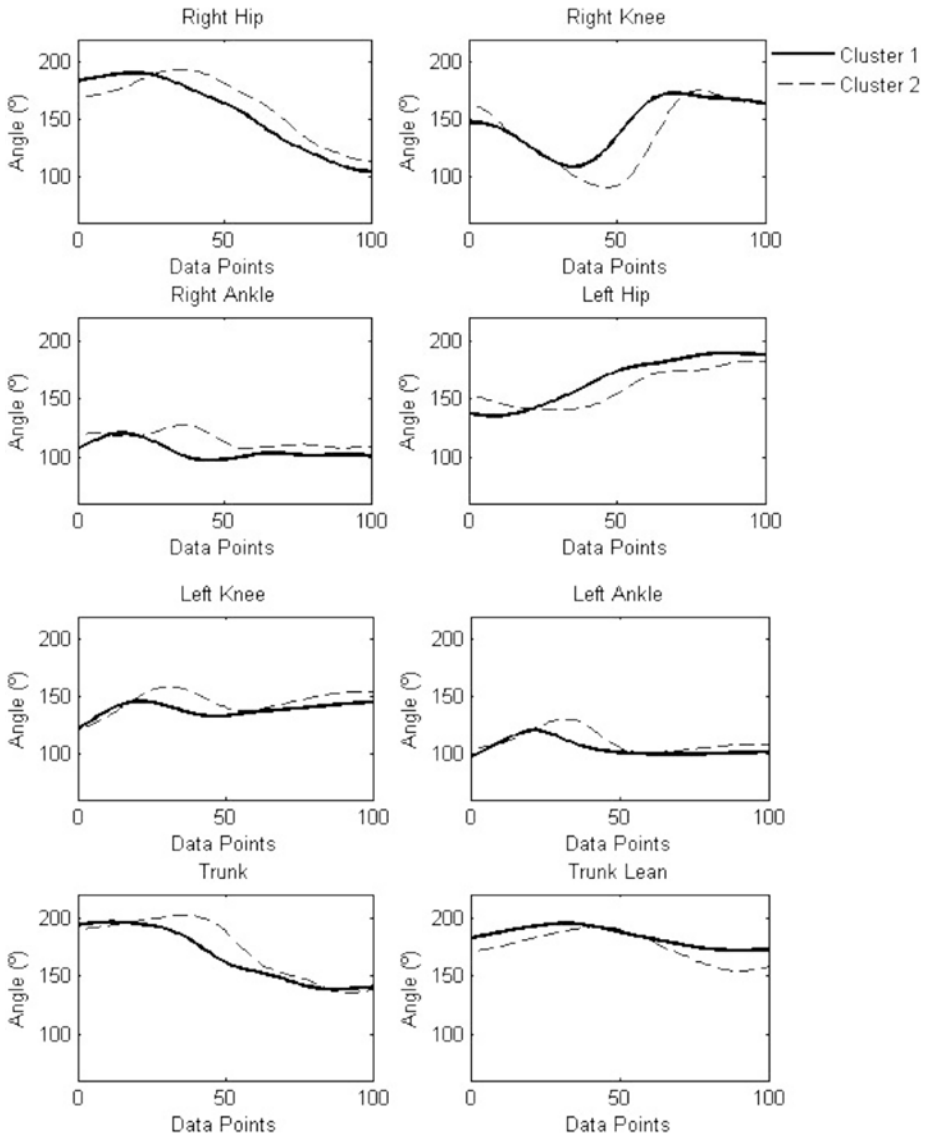


Figure 5 — Plots of individual kinematic variable input between clusters 1 and 2 for Participant YH.

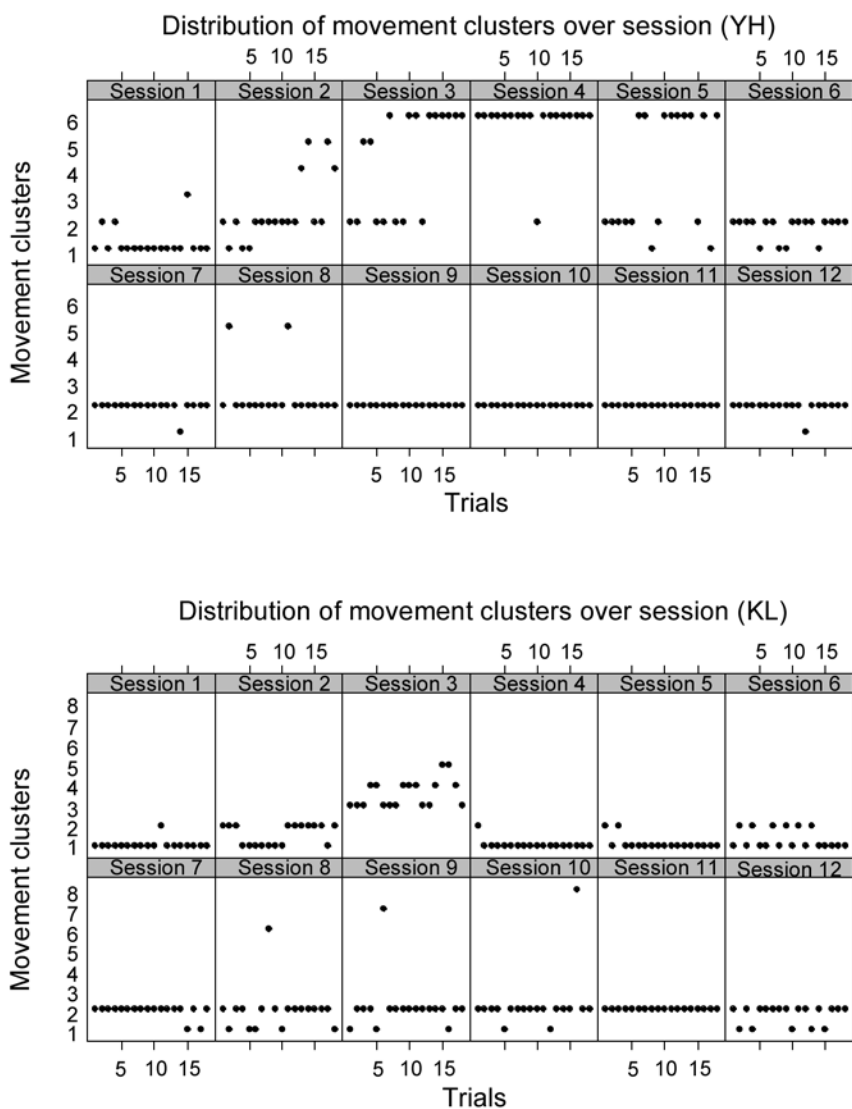


Figure 6 — Distribution of movement clusters over practice sessions for all participants. Number of trials per session is shown on the *x* axis. Movement clusters for each session are shown on the *y* axis.

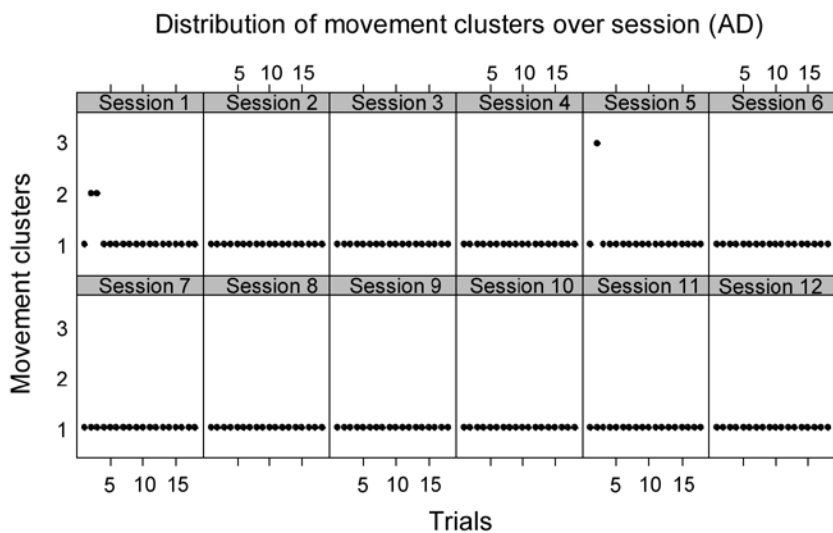
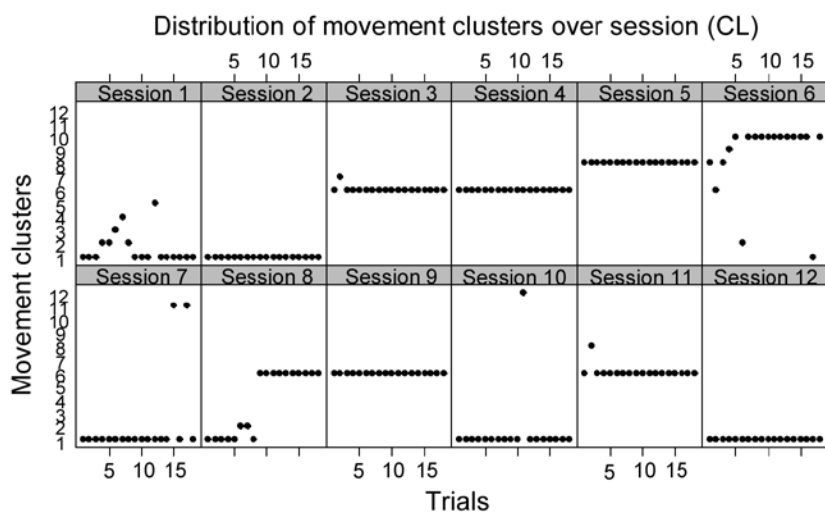


Figure 6 (continued)

YH used mainly cluster movement C1 in session 1 before exploring four different movement patterns (C1, C2, C4, and C5) in session 2. Increasing variability, expressed in the number of movement clusters used, was observed within sessions 2 (SR = 0.529) and 3 (SR = 0.412). Cluster C6 was preferred at session 4 (SR = 0.11, 94% occurrence).

Similarly, increasing variability in movement clusters within session 5 (SR = 0.471) was observed before the use of C2 appeared to be preferred at session 7 (SR = 0.118, 94% occurrence; C2 at session 6 was lower than session 5 [SR = 0.353, 78% occurrence] but was still higher than at session 4). Thereafter, C2 was continually the preferred movement cluster from sessions 8 through 12 (SR = 0.235, 88–100% occurrence). From the results, some features of pattern transitions were observed in movement clusters between sessions 1 and 4, as well as between sessions 4 and 7. Specifically, increasing variability in use of movement clusters before a change to a preferred movement cluster was clearly evident in participant YH (e.g., from C1 to C6 and C6 to C2, respectively).

Participant KL

Hubert- Γ coefficient indicated the presence of 8 clusters with alpha values with $p \geq .90$. Cluster C1 was mainly used by participant KL in session 1 before alternating between C1 and C2 in session 2 (see Figure 6). The use of C3 appeared in session 3, but the switch ratio was higher for the session (SR = 0.471) before reverting back to the preferred movement cluster of C1 in sessions 4 (SR = 0.056, 94% occurrence) and 5 (SR = 0.235, 89% occurrence). Increasing variability in the use of movement clusters was observed in session 6 (SR = 0.706) before the reemergence of C2 as the preferred cluster in session 7 (with SR = 0.235, 89% occurrence). From sessions 7 through 12, mainly C1 and C2 were present. Higher variability was observed in session 8 (SR = 0.529) and session 12 (SR = 0.588). Although there was higher variability in the movement clusters used in session 8, C1 was still the preferred movement cluster from sessions 9 through 11.

Similar to participant YH, evidence of increased movement pattern variability before a transition between movement clusters was observed for participant KL. Certainly, a higher variability of movement clusters was observed at session 6 (SR = 0.706) during the transition between C1 (in session 5) and C2 (in session 7). However, there were also instances when a higher variability of movement clusters did not result in a change from one preferred movement cluster to another (e.g., in session 3 and session 8 with SR = 0.471 and 0.529, respectively).

Participant CL

Hubert- Γ coefficient indicated the presence of 12 clusters with alpha values with $p \geq .74$. There was higher movement cluster variability in session 1 (SR = 0.412) before C1 arose as the preferred movement cluster in session 2 (SR = 0, 100% occurrence). Subsequently, C7 replaced C1 as the preferred movement cluster from session 3 (SR = 0.118, 94% occurrence) to 4 (SR = 0, 100% occurrence; see Figure 6). A transition between movement clusters (C8) was observed in session 5 without a clear increase in variability between movement clusters before a change in sessions 3 or 4. A change from C8 to C10 was further observed within session 6. Thereafter, a switch back to C1 as the preferred movement cluster was present

during session 7, followed by another switch to C6 within session 8. From session 9 through 12, C1 and C6 were the preferred movement clusters, alternating between those sessions.

Interestingly, cluster C1 disappeared in early practice sessions before reemerging at sessions 7, 10, and 12. There were even signs of “regression” in the use of movement clusters (e.g., using C1 during early and late practice sessions). However, the performance outcome score was higher at session 10 and 12 for C1 than at session 2. Although C1 was used in early and late practice sessions, the higher performance outcome attained by participant CL could be explained by the greater consistency of the movement at ball contact. Additional analysis for participant CL on foot speed at ball contact appeared to be more consistent in sessions 10 (10.06 ± 0.39 m/s) and 12 (9.58 ± 0.31 m/s), compared with session 1 (10.04 ± 2.56 m/s).

There was some evidence of higher variability of movement clusters within sessions, especially sessions 1 (SR = 0.412) and 6 (SR = 0.471). But, in general, SR was low or close to zero for most practice sessions. Distinctive use of movement clusters was observed *between* sessions (e.g., sessions 2–3 and sessions 9–10) without any variability in the use of movement clusters *within* sessions. Other than the change from C8 (session 5) to C1 (session 7), where higher variability of movement clusters was present in session 6 (SR = 0.471), participant CL did not demonstrate a clear trend in variability of movement clusters *within* sessions before transitions.

Participant AD

From the Hubert- Γ coefficient, presence of 10 movement clusters was determined. However, alpha values from the multiscale bootstrapping procedure were not as high as for other participants, being only .57 at one of the major branches in the clustering tree. This finding suggests that clusters belonging to that branch might not have been a true clustering of trials because the observed subclusters might not have been different. It was then determined, based on the need to accept higher alpha values (where $p = .94$ in this dendrogram), that three clusters would be a more accurate clustering of the data set. Such a decision was made to preserve the stringency for interpreting the data to avoid biasness in suggesting a conclusion that might not be true. For participant AD, mainly one cluster of movement (C1) was used throughout the practice phase in this study. Clusters C2 and C3 appeared only in sessions 1 and 5. There was no evidence of any variability of movement clusters within or between practice sessions (see Figure 6).

Discussion

The aim of this article was to investigate learning of discrete multiarticular actions in neurobiological systems by examining (a) the presence of transitions between preferred movement clusters during practice and (b) the presence of increasing variability in movement pattern clusters accompanying a transition in preferred movements during practice. To summarize the main findings, all participants showed evidence of change between preferred movement clusters and higher variability in the use of movement clusters within a session except for participant AD. Data showed that participants YH, KL, and CL evidenced change between preferred

movement clusters and high variability of movement clusters within sessions. One participant showed consistent evidence of variable movement clusters within sessions before a change in preferred movement clusters, and two others showed mixed trends in this feature of learning. However, there were instances when increasing variability in movement clusters was not accompanied by transition from one preferred movement cluster to another. Moreover, distinct changes in different movement clusters between two neighboring practice sessions, without the presence of any variability in movement clusters in either of the two sessions, were sometimes observed (participant CL). One participant showed little evidence of movement pattern exploration during practice (participant AD), failing to show preferred movement cluster changes, as well as variability in movement clusters used within or between sessions. As expected, performance improved in all participants as a function of practice.

Participant YH showed clear changes between preferred movement clusters and presence of variability before acquiring a preferred movement cluster within sessions. Specifically, the presence of higher levels of variability highlighted the functional role of movement variability during exploratory practice. Findings from the current study, when referenced to Liu et al.'s (2006) study on learning a novel roller ball task, also showed similarities in terms of the presence of increased variability before a change in movement patterns for successful learners. Variability in movement clusters afforded flexibility and adaptability in exploring functional movement solutions when attempting to satisfy specific task goals (see also Riley & Turvey, 2002). These findings suggest that movement variability is an important mechanism for strategically developing new ways to solve coordination problems and that behavioral variability can also lead to the discovery and selection of new cognitive-motor strategies (Siegler, 2000; Summers, 1998). Observations of changes in preferred movement clusters following high variability of clusters used supports the conceptualization of motor learning as an exploratory process (see Bernstein, 1967). It seems that movement stability might be traded off to help learners discover new patterns of coordination, and this was evident especially for participant YH. These behavioral trends were also observed to a lesser extent in participants KL and CL.

In the case of participant KL, there were occasions when high variability in movement clusters did not effect a change in preferred movement clusters in subsequent practice sessions. In this case, it was possible that the level of variability exhibited might not have been of sufficient magnitude to effect a change between preferred movement clusters. The absence of a transition to a new movement pattern even with increased variability can still be seen as a reflection of exploratory behavior. However, from a dynamical systems perspective, only a local search was conducted around the original preferred movement pattern that did not result in a successful assembly of a new movement pattern in the epigenetic landscape (Liu et al., 2006). It is notable that the switch ratio (SR) in sessions in which a change in preferred movement clusters followed in subsequent sessions was higher than in sessions in which a subsequent change in preferred movement cluster failed to occur (e.g., SR = 0.706 for session 6 compared with SR = 0.471 and 0.529 for sessions 3 and 8). The mechanism of learning in the absence of transitional behavior between preferred movement clusters requires further investigation.

A lack of variability in movement clusters within sessions was also observed for participants CL and AD. Similarly, in Liu et al. (2006), no changes, either discontinuous or continuous, were observed in movement dynamics adaptations for less successful learners. It is possible that intentions and informational constraints in meeting the task goal had an impact on the nature of change in the movement clusters shown by participants CL and AD. For participant CL, distinct movement clusters occurred mainly between sessions and very little variability in movement clusters was observed within each session. From the strip-plots between movement clusters and practice sessions, it seems likely that participant CL could have selected a movement strategy based on experiences from the previous practice session(s). Elsewhere, it has been acknowledged that the pathway of coordination changes is dependent on the task goal (Ko et al., 2003; Newell & McDonald, 1994). Information in the form of feedback or instructions shapes the intention of the learner, and these influences are important in helping us understand how coordination solutions evolve and how the task goal helps to direct learners toward specific movement behaviors (Jirsa & Kelso, 2004). Clearly self-reporting techniques would be necessary in future research to ascertain whether participants employ different cognitive strategies to satisfy task constraints resulting in intentional constraints actually overriding existing coordination dynamics.

For participant CL, there was some evidence of "insight learning," in which abrupt transitions in movement patterns occur (see Nourrit et al., 2003). It is likely that, for many learners, abrupt transition of movement patterns with high variability in movements as described in bimanual finger coordination studies might be infrequently observed during complex skill acquisition (Nourrit et al., 2003). Regardless, it is clear that learning is an intentional process, with future goals determining the changes a learner undergoes. In this study, there were two main intentional constraints: (a) one specifying the goal of the action (e.g., getting the ball over the bar) and (b) another specifying the goal of learning (i.e., become more skilled; see Schmidt & Fitzpatrick, 1996). Learning should, therefore, also be viewed as a process of searching the important constraints on performance, including those arising from task specificity and the interaction between physical and informational constraints (Rosengren, Savelsbergh, & van der Kamp, 2003). For participant CL, a nonlinear and sudden change between preferred movement patterns was established in some instances in the absence of high variability in movement clusters, and this could have been the consequence of the influence of behavioral information available in the learning context.

It was also noted how regression to previously explored movement clusters occurred, especially in participant CL (cluster 1 in session 1 and also in session 12). Why regress to previous clusters of movement? Again, a likely constraint on motor learning could have been the specific intentions involved in the process of change in the use of movement clusters. Possibly, participant CL realized that there were certain features of previously used movement solutions that might have been effective through exploration of the perceptual motor workspace during practice, although no assessment of explicit knowledge acquisition was administered in this study to confirm this suggestion. Reparameterizing certain aspects of cluster movement C1 could be observed as an appropriate movement solution for participant CL in achieving the task goal by the end of the practice phase. Participant CL seems to have acquired better control of the use of movement cluster C1 later

in practice compared with using the same cluster in session 1, as evidenced by the more consistent foot speed values at ball contact in the later practice sessions. Certainly, this proposition requires investigation in future studies.

Participant AD showed little change in the clusters of movement used, and this lack of movement variability could have been an indication of the lack of effective exploration of the perceptual motor workspace. The lack of search activity was reflected through the absence of observed variability in the movement clusters used and was associated with a smaller rate of improvement between pre- and posttest sessions for this individual. Similarly, in Liu et al. (2006), no changes, either discontinuous or continuous, were observed in movement dynamics adaptations for less successful learners, as was apparent for participant AD in the current study.

It was also interesting to observe that there was no distinct decrease in performance outcome during transition between preferred movement patterns (a decrease would be expected because participants were exploring for possible movement solutions and this would have affected performance). Moreover, there was also no clear trend for improved performance scores after a new preferred movement cluster was acquired, even though performance scores did increase as a function of practice. It is possible that further functional parameterization of the movement cluster is required before performance improvement can be seen. Alternatively, future performance measures could incorporate error distance values to increase the sensitivity of the performance outcome measures to better reflect changes in functional differences after a transition between preferred movement clusters. However, the measurement of error distances alone would not be possible in this study because some of the passes would have contacted the live receiver before landing on the ground. Nevertheless, these issues pertaining to providing a clearer link between performance changes and acquisition of new preferred movement clusters can provide stronger evidence for examining the process of transition between preferred movement clusters as described in concepts based on nonlinear dynamics in future work.

In conclusion, this study has shown that progression of learning is different between individuals because it is dependent on the interaction between the learner and available behavioral information, which is unique for each individual. There was also some indication that high variability in movement clusters can (but not necessarily) accompany a change between preferred movement clusters. Compared with learning in bimanual finger coordination tasks, the target pattern is unlikely to be immediately available in discrete multiarticular actions, because the pathway of change during learning is not easily predictable. Degeneracy, where different functional coordination solutions can be explored under the same task demands (see Hong & Newell, 2006), is omni-present during the learning of multiarticular movements. Based on the data from this study, it can be suggested that observing the nature of changes during practice might reveal insights into how movement variability can be used for adapting and refining complex multiarticular discrete actions during learning. The interpretation of the data was based on a stringent application of the cluster analysis procedure, and more work should also be done on examining the use of such cluster analysis tools for other movement models as well as experimental conditions.

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