Searching Strategies in Practice: The Role of Stability in the Performer-Task Interaction

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Through the view of the search strategies approach to skill acquisition–and its dynamic systems theoretical background–non-local changes in behavior are expected to emerge through a process of decreased stability (increased variability) of the ongoing movement pattern as to allow exploration of new regions of the perceptual-motor workspace. However, previous studies have not found such relation; only in non-redundant tasks. We believe that such issue occurs because these previous studies have focused on the movement pattern variability while in redundant tasks the variability that matters is at the task space level. Therefore, we analyzed the data of 15 individuals that practiced a throwing task for five days in terms of their movement patterns and release parameters to test whether increased variability at the task level was predictive of non-local changes in practice. We found that, for non-local changes at both release parameters and movement pattern levels, performance and performance variability were significant predictors. We discuss these results highlighting that they support a strong assumption of the search strategies approach, corroborate to the dynamical systems view on motor learning, and pointing the lack of consideration of non-local changes in other theories of motor learning.

Keywords: motor learning, variability, dynamical systems, exploration, skill acquisition

Introduction

For every attempt to perform a motor task successfully, the learner attends to perceptual variables of the environment and act attempting to achieve the best performance. This continuous process of performing the task provides information of how the employed perception-action cycle relates to task performance. Through this process, the learner finds other perceptual variables that relate to important aspects of the task and, as well, find new movement coordination patterns that can lead to better results. When the perception-action cycle is in harmony with the requirements of the task, good performance becomes repeatable and learning is said to have occurred (Shaw & Alley, 1985). Given the perception-action cycle is in tune to important aspects of the task, variations of the task are easily followed by adaptations in behavior and adaptability is evident.

In this continuous search for adaptable solutions, learners inevitably leave initial regions of the perceptual-motor workspace given its incapacity to achieve the goal of the task. The perceptual-motor workspace refers to the whole layout of stable and unstable perception-action cycles that individuals might attempt to engage on. The learner, then, in perceiving the incapacity of the current perception-action coupling to maintain or achieve high levels of performance, moves to other regions of the perceptual-motor workspace. The question is how this search process occurs.

Following the dynamic systems (DS) perspective on motor behavior (Kugler et al., 1980; Kugler & Turvey, 1987), the learner can be viewed as a system interacting with patterned information coming from the environment and task (Newell, 1986). According to the search-strategies approach (SSA) (Newell et al., 1989; Pacheco et al., 2019), the interaction with the task is of great importance in driving change in motor learning. It is the interaction between the learner and the task – specifically the task space layout – that guides the learner on how and where to change (see Pacheco, Lafe, and Newell 2019 for a review).

Three main pathways of motor learning have been highlighted in DS literature: a parametrization, a shift, and a bifurcation (discussed, respectively, in Newell 1985 and Kostrubiec et al. 2012). The first two pathways can be combined into a single idea of specifically tuning "parameters" of the perception-action coupling to achieve the task goal. This "tuning" process is viewed in SSA as a gradient descent (or local search) process to a region where the individual reaches the best possible result that the interaction between perceptual-motor workspace and task space allow. Despite the fact that specificities of this process are still in dispute (see Jacobs et al. 2011; Pacheco and Newell 2018), tasks that require such small adjustments are the most studied in the literature.

The learner, however, does not only search continuously through the perceptual-motor workspace, non-local changes (or "jumps") are observed through practice. These are usually observed when the movement variables change independent of the task gradient surrounding it and with larger magnitude. Non-local changes in the search process are far less studied despite the fact that earlier researchers called attention for its necessity (see Gelfand and Tsetlin 1962). The requirement for non-local changes comes from the fact that learners might not achieve good performance at first attempts in new tasks given the inadequacy of its initial perception-action couplings. Thus, small adjustments in either informational variables attended or movement aspects would not lead to good solutions.

From DS, such non-local changes occur given learners would intentionally act against its intrinsic tendencies to maintain a perception-action coupling and would, following the dynamics of his/her perceptual-motor workspace, land on other regions (see Scholz and Kelso 1990), starting local search again. As the learner attempts to practice in unstable regions of the perceptual-motor workspace, a process of stabilization of this region occurs (see Pacheco and Newell 2015). When the perceptual-motor workspace demonstrates a new stable region, a bifurcation process took place as there is a new attractor in the layout of perception-action couplings (Kostrubiec et al., 2012; Zanone & Kelso, 1994). Bifurcation in learning has been demonstrated many times (e.g. Liu and Newell 2015; Brakke and Pacheco 2019; Zanone and Kelso 1992) and can be argued to be the learning pathway that bases all changes in movement pattern coordination. In accordance to the aforementioned rationale, the pattern of non-local change would be of increased variability in the initial pattern – decreased stability – and then a change to new patterns of coordination.

However, all the tasks that demonstrated such pattern were tasks on which the movement pattern coordination is tightly closed to the task performance: either the task *is* to perform a given movement pattern or the movement patterns allowed are overly similar (see Liu, Chuang, and Newell 2019). Although these tasks represent some share of what is performed by humans (e.g., choreography, gymnastics), most activities can be said to be *redundant*: tasks that the goal can be achieved through many movement patterns (for discussions on the topic see Latash 2012; Sternad 2018). Chow et al. (2008), to the best of our knowledge, is the only study that tried to study whether non-local changes in movement patterns occurred through a process of increased instability in the previous movement pattern eliciting changes to new ones in a redundant task (kicking a ball to a target). They performed cluster analyses to classify different movement patterns presented during practice and, observing learners' variability in performing these clusters, attempted to relate variability to change in movement patterns mode over time. However, they failed to corroborate enhanced variability leading to non-local changes.

Are redundant tasks of a different nature in that decreased stability is not the mechanism underlying non-local changes in search? In a first look, it is true that redundant tasks have the important distinction from non-redundant tasks in that the perceptual-motor workspace differentiates from the task space – performance is not determined by movement pattern. However, decreased stability could still be the mechanism for change; the difference is at the level that researchers should pay attention to capture the process. As we described before, it is the interaction with the task space that offers information on how to change to achieve a goal; variability at the movement coordination level is “irrelevant” if it does not relate to task performance variability. In fact, this type of variability in movement pattern that does not disturb performance has been demonstrated to be exploited by learners (Bernstein, 1967; Latash, 2010) and is even said to stabilize performance (Golenia et al., 2018; Latash et al., 2007; Scholz & Schöner, 1999). Thus, we believe that increased variability (decrease in stability) before a transition would be observed not at the movement coordination pattern level, but in the interaction between learner (and the movement coordination pattern) with the task space level.

Indeed, previous papers on SSA showed that variability at the level of the task space was determinant for performers to find the best solution of the task. Pacheco and colleagues (Pacheco et al., 2017, 2020) showed that non-local changes in strategy occurred *after* increased variability in performance. However, these studies cannot be considered conclusive in this matter. Pacheco, Hsieh, and Newell (2017) elaborated task conditions on which variability was *necessary* for individuals to perceive the inefficiency of initial solutions and find the most appropriate solution. Both studies required individuals to perform tasks on which non-local changes were *necessary* for the task goal to be achieved. Thus, it could still be that results supporting the pathway of decreased stability to non-local change hold only for non-redundant tasks when individuals start far from the most appropriate solution.

Therefore, it is the goal of the present paper to test whether non-local changes in practice would occur as a function of increased variability (decreased stability). In this paper, we reanalyzed data from Pacheco and Newell (2018a) on which individuals performed throwing for precision (threw plastic golf balls into a target) for five days. In that study, the authors analyzed whether individuals performing the same practice condition would demonstrate similar end-state performance and transfer. Here, we take advantage of the multi-level nature of the task and analyze the data from all five days in practice to test whether individuals non-locally changed through the perceptual-motor workspace considering the movement pattern employed, as well as non-local changes at the release parameters level. In this way, we can consider whether movement pattern variability, or the task-space variability (i.e., landing position, number of hits) relates to non-local changes in the two level of analysis of the task (i.e., release parameters and movement pattern). We also take the opportunity to describe the local search patterns demonstrated between non-local changes.

Methods

This study reanalyzes the data from Pacheco and Newell (2018a) paper. Thus, we briefly describe their methods here

Participants

From the 17 participants of the previous study, we only analyzed 15 participants as two participants require a thorough relabeling of the markers in the VICON software. The 15 participants were college-level students (age: 24.7 ± 3.4, 8 females).

Task, Apparatus and Procedures

The task was to throw a plastic golf ball into a triangle-shaped target of 15 cm height and 22.8 cm for each side. The target was made of carboard and was placed on a table of 73 cm height with its center point at 2.05 m of distance from the participant. The target was placed in a way that one of the vertices was pointing at the participant's direction.

To record the participant's movement patterns, all trials were recorded using the VICON system (sampling rate: 100 Hz). The participant wore a dark tight shirt and had markers placed on their right arm and trunk following the Plug-in Gait marker localization: spinous process of the seventh cervical vertebra, spinous process of the 10th thoracic vertebra, jugular notch where the clavicula meet the sternum, xiphoid process of the sternum, right scapula, acromion-clavicular joint, lower lateral one-third surface of the right arm, lateral epicondyle, lower lateral one-third surface of the right forearm, thumb-side of the wrist, little-finger side of the wrist, and middle knuckle on the right hand. To measure the release parameters, the balls were also marked. The balls were first covered with black tape and four markers were glued to the ball.

On the first day, the participant read and signed the informed consent form and had the markers placed on his/her body. The instructions emphasized that the participants were not restricted to throw using a specified movement pattern but could explore different movement patterns as long as this exploration had the goal to improve performance.

The participants practiced for 210 trials on each day. The experiment took five days (a total of 1050 trials). One participant only performed four days of practice (first, second, fourth and fifth day of the regular schedule) because of technical issues. Provided the current analyses are not dependent on the day of practice, we maintained her for our analyses.

During practice, the participant would receive a set of 6 balls at a time. After each set, the experimenter counted the number of hits and informed the participant. After 30 trials, the experimenter summed up the performance of the last 5 sets of 6 balls and provided the score to the participant. If any individual required rest, a break was provided.

Data Analysis

The data of the digitized positions of the markers was processed as follows. In the

Nexus 2.11 software, the gaps were filled in through three rigid body filling gap procedure (for hip, trunk and ball markers), two pattern filling gap procedure (for wrist and elbow markers), and a Woltring filling gap procedure for all markers. Then, the skeleton joint and marker statistics were calculated in a built-in pipeline. In Matlab R2020b, a script was developed to fill the reminiscent gaps through a spline (function spline), and the data were low-pass filtered with a Butterworth filter (10 Hz cut-off, 2nd order).

A few trials were discarded because of technical issues (i.e., markers not being recorded, markers falling, etc.). This represented 190 trials out of 15540 analyzed here (1.22%).

Release Parameters

To identify the release parameters of the throw (i.e., position and velocity of the ball at the moment of release), we determined the moment at which the distance between ball and hand crossed the threshold of 6 standard deviations. For each trial, we averaged the markers that relate to the hand (thumb-side of the wrist, little-finger side of the wrist, and middle knuckle on the right hand) and the markers that relate to the ball to have a single 3D location of the hand and the ball in space. Then, the Euclidean distance between hand and ball was calculated. To identify the ball-hand distance before the release, we calculated the average and standard deviation of the ball-hand distance considering 50% of the whole trajectory recorded. This average value was considered the "holding" ball-hand distance. To identify the release position and velocity, we identified the moment in which the ball-hand distance was above the "holding" value by 6 standard deviations and was maintained that way up to the end of the trial. Such large threshold was to avoid selection of the wrong release parameter given manipulation of the ball in the participant's hand. The release velocity was calculated using the procedure described in Winter (2009).

Movement Pattern

To facilitate the identification of different movement patterns by the cluster analysis, we used the hand trajectory during the trial as input. The hand trajectory was selected as the moment on which the hand as at the most posterior position in the antero-posterior before the release parameter – indicating the beginning of the motion forward of the arm to release the ball. The end of the trajectory was selected as 300 ms after the throw (30 frames after the release). The trajectory was time normalized using the spline function to have the time ranging from 1 to 100% of the trajectory.

Movement Pattern Clusters

To identify discontinuous changes at the movement pattern level, we employed a cluster analysis. The idea is that the cluster analysis is able to identify sets of movement patterns that are more similar within than in between. That is, the analysis would identify qualitatively different sets of movement patterns. In terms of our goal here, if individuals changed to a *different* region of the perceptual-motor workspace, the movement pattern at trial t would be qualitatively different than the movement pattern at trial t-1. This change would be characterized as movement pattern in trial t belonging to cluster c_1 while the movement pattern in trial t-1 belonging to cluster c_2. Given this change is not a *mere* adaptation of a given movement pattern, but a change to a *new one*, we considered such change as a discontinuous change at the movement pattern level.

In order to identify movement pattern clusters (i.e., different regions of the perceptual-motor workspace in terms of the hand trajectories), we included, in a single matrix, the hand trajectories for each trial for all days and subjects. Then, we evaluated how many clusters (from 1 to 10) would be required using the *evalclusters* function in Matlab considering the *linkage* method and the *silhouette* criterion. The maximum of 10 clusters was arbitrary. We expected a maximum of three clusters (overhand throw, underhand throw, and toss) but we did not want to influence the outcome by imposing this limit. Thus, we considered up to 10 clusters as to allow the algorithm to find more clusters than we initially considered. The Silhouette criterion consider the similarity of each datum to data in its own cluster, when compared to data in other clusters. The observed number of clusters was then used as input to the *clusterdata* function using the *linkage* method and *ward* algorithm.

Non-Local Changes

At the movement pattern level, any trial that belonged to a different cluster classification than the previous one indicated a non-local change.

At the release parameter level, we performed the same routine described in Pacheco, Lafe, and Newell (2020). First, we identified abrupt changes in the linear trend of the release parameters (considering all six dimensions) over time using the *findchangepts* function in Matlab. Figure 1 shows a schematic of the analysis. This function searches for sections in the data to minimize the deviations of the data to a chosen statistic. We chose the linear trend of all six dimensions. We tested whether the data was better explained considering from 1 to 21 sections in the data (with a minimum of 10 trials per section). The maximum number of sections was defined in terms of the minimum number of trials. The minimum of trials, however, is somewhat arbitrary. This was what we considered to be enough to identify any type of trend in search (less trials could lead to spurious trends) without imposing too long sections in the search. For the analyses, the selected number of sections was based on the criterion that adding one more did not decrease the residual (the deviations of the data from the linear trend).

(Figure 1 around here)

Then, these moments of abrupt changes in the linear trend were evaluated to see whether they referred to changes only in the linear trend or were also related to changes in the perceptual-motor workspace region (see Pacheco, Lafe, and Newell 2020 for a thorough explanation of the method). For this, we calculated the Euclidean distance between each data pair in time considering the ten trials before and the ten trials after the abrupt change to have an estimate of within-section change and compared it with the Euclidean distance of the trials at the abrupt change (between-section change). This was done by comparing the mean of the within-section change data against the between-section change through a bootstrap procedure (1000 iterations) using the *bootstrp* function of Matlab. If 95% of the mean distribution of the within-section change was above the between-section change, the given abrupt change was considered as a non-local change at the release parameter level.

As expected, any non-local change at the movement pattern level was associated with a non-local change at the release parameter level. The opposite was not true.

Local Changes

Considering the sections in between abrupt changes, we followed Pacheco, Lafe, and Newell (2020) and tried to qualify the linear trends in terms of "change" (linear trends in the release parameters leading to changes in the throw distance), "covariation" (linear trends in the release parameters that compensate not leading to changes in the throw distance), or "maintenance" (no linear trends in the release parameters) (see Figure 1). For this, first, we calculated the landing position (two dimensions) of the ball based on the release parameters and the height of the target. Then, we performed, for each section within abrupt changes, a bootstrap (1000 iterations) estimating the linear trend on the two dimensions of landing of the ball, and on the six dimensions of the release parameters. If the linear trend on any of the two dimensions of landing was shown to be significant, we classified the section with a pattern of "change". If a linear trend on any of the six dimensions was shown to be significant (with no linear trend on landing), we classified the section with a pattern of "covariation". Else, we classified the section with a pattern of "maintenance". Interestingly, and contrary to Pacheco, Lafe, and Newell (2020), we found only patterns of "maintenance". This could be expected as their study employed a search task – something that might have induced such types of search.

We decided to consider the approach used in Pacheco and Newell (2015). In their study, they evaluated whether individuals were employing (in average) a more exploratory or corrective (positive or negative feedback) strategy in their trial-to-trial change. They employed the autocorrelation (lag 1) to evaluate such possibility. The idea that a positive autocorrelation relates to exploration comes from the fact that individuals drifting away from the current position (continuously) show a positive autocorrelation. However, if the individual is oscillating around a point (decreasing the deviations over time), then the autocorrelation is negative. To calculate this, we performed a principal component analysis on the three-dimensional release velocity time series of each section and performed an autocorrelation on the eigenvalue of the first two principal components. The choices for the release velocity and the first two principal components follow Pacheco and Newell (2018a) that showed that the release velocity was the main predictor of changes in the landing position.

Variability

To test whether the variability in the interaction between the individual and the task space would predict non-local changes in the search process in practice, we calculated three measures of variability. The first two measures are the moving standard deviation (window of ten trials) of the longitudinal and transversal directions of the landing positions calculated through a function designed for this purpose. The third measure of variability was a moving variation range (window of ten trials) of the movement pattern. For the latter measure, we considered a 10-trial window. We calculated the 9-dimensional (joints) sphere of the 10 trials around its centroid. Figure 2 shows a schematic of the analysis (see also Allen et al., 2019). This was performed for each time-window of 5% (from 1 to 100% normalized time). Then, we averaged the variability for all time-windows to represent the variability of this 10-trials-window. To calculate the summed distances to the centroid, we used the *kmeans* function in Matlab. Additionally, we also got the moving average performance of a window of 10 trials that could range from 0 (no hits) to 1 (hits in all trials) – this measure provides a proportion of hits at that window.

(Figure 2 around here)

In order to relate variability to non-local changes, we performed the moving windows described above in terms of the non-local changes observed. That is, we always related the non-local changes (either in release parameters or joint changes) to the 10-trials window that preceded them. To do this, we first identified all moments of non-local changes and, for each one, sequentially, we calculated the variability measures of the preceding window up to the beginning of the day section or (if we are referring to the second or later non-local change) to the previous non-local change.

Statistical Analysis

First, we described the change dynamics of all individuals in terms of performance per block (30 trials) and per day. We summed up the hits for each 30 trials and performed a linear mixed-effect analysis with blocks and days as independent variables (in both fixed and random parameters).

Second, we show descriptively the frequency of non-local changes, the cluster analysis results and the characteristics of the local search of each individual throughout practice. We also performed linear mixed-effect analyses with blocks and days as independent variables (in both fixed and random parameters) for the autocorrelation (lag 1) values of the first and second principal component eigenvalues to explore whether there were any changes through days.

Finally, to test the relation between variability and non-local changes in the release parameters, we tested whether non-local changes in the release parameters would be predicted by variability at the landing positions and performance (hit proportion) (Figure 3 shows a schematic of the analysis). For this, we used non-local changes as dependent variable and days, variability in longitudinal and transversal directions, and hit proportion as independent variables in a general linear mixed-effect analysis with binomial distribution. For non-local changes in the movement pattern, we performed the same analysis with the same independent variables. Additionally, we also performed another analysis including the variability in the movement pattern as a predictor. In this way, we did not only test our hypothesis, but also consider whether variability at the movement pattern could also contribute to non-local changes in movement patterns.

(Figure 3 around here)

For all linear mixed-effect analyses, we used the *fitlme* or *fitglme* functions in Matlab for linear and general linear mixed effects, respectively. Also, we maintained all fixed effects to show which were or not significant but, for the random effects, we performed a backward procedure to eliminate random effects not necessary to the model. All analyses considered significance at $p < .050$ and we used the R^2 as our measure of effect size – considering values above 0.25 as large, 0.09 as medium, and 0.01 as small (Field, 2009).

Results

Performance

Figure 4 shows the change in performance as a function of practice (block and days) for each individual. As can be observed, there is high variability between individuals; this supports the use of linear mixed-effect analysis in the present case.

(Figure 4 around here)

The analysis showed an average value of 9.73 hits for the first day and block (standard error ± 0.91; t [515] = 10.76; $p < .001$), significant improvement in performance in terms of blocks (0.34 ± 0.06 per block; t [515] = 5.42; $p < .001$), and days (0.34 ± 0.17 per day; t [515] = 1.99; $p = .047$). The random effects demonstrated significant variation for the starting performance (3.32 ± 1.04) and improvement per day (0.56 ± 0.22). The R^2 was of 0.65 (large effect).

Identifying Non-Local Changes

The cluster analyses resulted in only two clusters of movement patterns representing, mainly, overhand and underhand throw. Figure 5 shows exemplary shoulder and elbow flexion angles for cluster 1 (underhand pattern; Figures 5.a and b) and 2 (overhand pattern; Figures 5.c and d) far from (a and c) and close to (b and d) a non-local change between clusters (i.e., change from one movement pattern to another). Such non-local changes occurred occasionally (maximum of 5 times per participant) and for 9 participants only.

Non-local changes at the release parameters level, however, occurred much more often. Figure 6 shows an example of non-local change at the release parameter level observed by an abrupt change in velocity (in the *y* and *z* axes). Such non-local changes occurred for all participants, with an average of 34.4 ± 17.33 times per individual. Additionally, as stated in the Methods section, all non-local changes at the movement pattern level were accompanied by non-local changes at the release parameter level.

(Figures 5 and 6 around here)

Characterizing Local Change

After identifying the non-local changes at the release parameter level, we observed, as stated in the methods, that no individual demonstrated linear trends in terms of the landing position (neither on the antero-posterior nor medio-lateral directions) or the release parameters. Therefore, we went to characterize the trial-to-trial relations in terms of the autocorrelation (lag 1) within sections between abrupt changes.

Figure 7 shows the average autocorrelation (lag 1) for each individual per day. Interestingly, there is also not a clear pattern for the autocorrelations for both first and second components (i.e., all autocorrelations were around 0). Given these results, we refrained from performing the linear mixed-effect analyses for the local change patterns.

(Figure 7 around here)

Increased Variability (Decreased Stability) and Non-Local Changes

Non-Local Changes at the Release Parameter Level

In order to test whether the increased variability (decreased stability) predicted non-local changes, we first tested whether variability at the landing positions or hit proportion would predict non-local changes at the release parameter level. The general linear mixed-effect analysis showed that, first, there was a higher change for non-local changes to occur at the first day of practice (estimate[1]: 1.96 ± 0.93; chance of 0.87; t [1515] = 2.10; p = .035) with such chance decreasing per day (estimate: -0.28 ± 0.05; chance of 0.7 in the fifth day; t [1515] = 5.53; p < .001). For the variability measures, no landing position variability showed any significant effect on the chance of non-local changes (p's > .849). However, non-local changes were significantly modulated by the hit proportion with high performances decreasing the chance of non-local changes (estimate: -5.78 ± 1.90; decrease chance to 0.02; t [1515] = 3.04; p = .002). The R^2 was of 0.56 (large effect).

Non-Local Changes at the Movement Pattern Level

Finally, in order to test whether non-local changes at the movement pattern level are predicted by increased variability (decreased stability) in terms of the interaction between the learner and the task space or *also* by the movement pattern variability, we performed two linear mixed-effect analyses considering only task related variability (and days) and adding the movement pattern variability. The model with only task related variability showed individuals started practice with a lower than chance occurrence of non-local changes (estimate: -2.29 ± 0.96; chance of 0.09; t [1540] = 2.39; p = .016) and decreased more such change over days (estimate: -0.66 ± 0.20; chance of 0.01 in the fifth day; t [1540] = 3.29; p = .001). The landing variability

[1] The estimate is the value that comes out from the equation. We also added the "chance" given the estimate comes from the linear part of the logit equation. Thus, we can calculate how each estimate relates to the chance of non-local changes occurrence.

measure in the antero-posterior direction showed no significant influence (p = .742). However, the landing variability measure in the medio-lateral direction showed significance with a positive relation: more variability increased the chance on non-local changes in movement pattern (estimate: 18.58 ± 9.40; considering the mean plus one standard deviation of this measure distribution, increase of the chance to 0.39; t [1540] = 1.97; p = .048). Additionally, the hit proportion also related to non-local changes in similar way as in the release parameter level (estimate: -6.09 ± 1.32; decrease in chance to less than 0.01; t [1540] = 4.62; p < .001). Adding the movement variability to the equation did not modify the significance of any other parameter while the movement variability, itself, did not show significant effect (p = .487). The R^2 of the former model (without movement pattern variability) was of 0.023 (a small effect).

However, there was a decrease in the BIC value (from 11923 to 11850) when adding the new variable. We decided, for the sake of exploration, to find the variables that would decrease the BIC value to the maximum in the current sample performing a backward method on the full model (including all variables). This was made iteratively to see which variables carried out higher weight on the BIC. We found that the minimum BIC was around 11607. Figure 8 shows the fitted model for two participants.

(Figure 8 around here)

In this model, the starting chance of non-local changes in movement pattern was below chance (estimate: -5.02 ± 0.77; chance of less than 0.01; t [1541] = 6.48, p < .001) with a further decreasing chance per day (estimate: -0.67 ± 0.20; t [1541] = 3.33; p < .001). The measures that stayed in the model were the variability in the landing position in the medio-lateral direction (estimate: 20.56 ± 8.56; chance increases up to 0.05; t [1541] = 2.40; p = .016) and movement variability, even not significant (estimate[2]: 0.16 ± 0.13; t [1541] = 1.18; p = .238). The random effects demonstrated significant variation in the starting chance of non-local changes (estimate: 0.66). The R^2 of this last model was 0.02 (a small effect).

Discussion

The present study tested whether non-local changes in practice would occur through a process of decreasing stability in the learner and task interaction. This decreased stability would be observed through an increase in variability in task outcome rather than the movement pattern variability. For this, we identified non-local changes in terms of movement patterns and release parameters in a throwing study and related them to variability at the landing positions, average performance (i.e., hit proportion) and movement pattern variability. We found support for our expectation in terms of both levels of analysis. In the discussion section, we discuss how these levels differed, the implications of such result for considerations on non-local changes in practice, what variability might be referring to, and discuss how our results fit in the extant literature on change in motor learning.

Non-Local Changes at the Release Parameter Level

Our results show that all participants performed a non-local change at the release parameters level at some point during practice. The chance of occurrence decreased through days but as shown in our results, it was considerably high up to the last day of practice. These non-local changes were related, according to our results, to decreased hit proportion.

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[2] The z-score of this measure was used.

This evidence for these changes during practice is important: few theories in motor learning consider such changes. If considered, these theories refer to these non-local changes as “changes in strategy” or “explicit” changes in motor learning (see, for instance, Taylor and Ivry 2012). These are generally pondered when experimental manipulations drastically modify the task (e.g., target position). In the present study, we saw non-local changes occurring in a constant target condition and, therefore, consideration on these so-called changes in strategy should be expanded for all types of tasks.

The occurrence of such type of non-local changes are in accordance to what was observed in previous studies from Pacheco and colleagues (Pacheco et al., 2017, 2020). Despite the different nature of these tasks, it is important to highlight the consistency of findings in observing non-local changes. It is important to note, however, that, in these other studies, the non-local changes were predicted by increase in variability in performance – not the average performance *per se*. It is possible that given the nature of the present task (on which the performance variable was dichotomous), average performance and variability in performance would be quite similar and, thus, we cannot differentiate both. In fact, the correlation between the two measures is around 0.5 (Pearson correlation) in the present study, which agrees, partially, to this argument.

Another issue is that the non-local changes in release parameters could occur within a given movement pattern. It means that participants would explore the different areas of the task space through non-local changes even when a single movement pattern is being performed. This reinforces the need for theories that consider only local changes to encompass such phenomenon. For instance, current ideas on motor learning – such as the Direct Learning (Jacobs et al., 2011; Jacobs & Michaels, 2007; Michaels et al., 2017) – assume continuous motion through the task space. In fact, we are tempted, given the results on the local-changes (discussed below) to question many interpretations from distributions in data believed to result from continuous motion through the task space. Is, for instance, the exploited redundancy in data something that arises from continuous drift (e.g., Cusumano, Mahoney, and Dingwell 2014) or non-local jumps along the goal-space?

Non-Local Changes at the Movement Pattern Level

Our results call for a role of learner-task space interaction in predicting non-local changes in movement pattern. Note that this holds independent of the two fitted models that we detailed in the results section – in that landing position and hit proportion were significant or when hit proportion is dropped from the model (see Figure 8). Given the latest model showed the lowest BIC, we consider it here for discussion.

As hinted in the Introduction section, non-local changes are an important part for solutions to be found in meaningful time during practice. Gelfand and Tsetlin (1962) provided arguments on time and computation power for how impracticable is to have an algorithm to find *the* best solution with so many degrees of freedom at play. These authors argue that individuals search for some satisfactory level of performance with a combination of local and non-local search. This combination is necessary considering the many local minima that arise from the perceptual-motor workspace and task space interaction (see also Schöllhorn et al. 2009 on the need of strategies to avoid local minima). Such process of non-local changes allow for individuals to visit a range of regions of the perceptual-motor workspace and task space supporting what was has been referred as the exploration and selection process in skill acquisition (Hadders-Algra, 2000; Thelen & Corbetta, 1994). The question was how such non-local changes are to occur.

Since the earlier studies from Kelso and colleagues (e.g., Schöner, Zanone, and Kelso 1992; Zanone and Kelso 1992, 1997) showing bifurcations in motor learning, there was the issue of finding other task paradigms that could illustrate all the "steps" that their approach required (e.g.,, finding order parameters) (see Newell and Liu *in press*). That is, how to show increased variation, abrupt changes and also new attractors in the perceptual-motor workspace in a new task? It might well be that the different routes through which researchers under the DS approach would study learning (see Beek and van Santvoord 1992) was an effect of the lack of task paradigms that could generalize these early findings.

One of the routes that appeared at the time was the SSA (Newell et al., 1989, 1991; Newell & McDonald, 1992). This approach was, at first, quite different from the "synergetic" approach from Kelso and colleagues in that it was not looking for order parameters, transitions and the like. As still under the DS approach, the SSA considered how perception-action coupling would maintain or decrease stability while viewing the whole process of skill acquisition as a process of search. Nevertheless, it was only recently that SSA went to explore how non-local changes could occur and explicitly related this type of motion in the perceptual-motor workspace to stability/variability (e.g., Pacheco, Lafe, and Newell 2019, 2020; Pacheco, Hsieh, and Newell 2017).

It is through an early consideration in SSA that such link can be made: "It is hypothesized that the information organisms use to search a perceptual-motor work space is a macroscopic property defining the 'form' of the layout of gradient and singular regions." (Newell et al. 1989, p. 102) That is, learners would perceive the layout gradient of the perceptual-motor workspace and act accordingly. In understanding that these early ideas encompassed, not explicitly, how the individual interacted with the task space also (see Pacheco, Lafe, and Newell 2019), that a connection between loss of stability and non-local changes in search was considered.

Thus, it was expected that Chow et al. (2008) would not find relations between movement variability and non-local changes when a redundant task was analyzed. It was at the task level (performance) that instabilities would arise as that is at that level that stability is attempted to be maintained. Variability in movement patterns that are "irrelevant" (redundant) to performance are not acted upon – specifically, if it does not relate to variability in performance, then it does not guide changes for the individual; a simpler explanation of why individuals, mostly, end up showing high variability in redundant spaces of the task space (see Martin, Reimann, and Schöner 2019; Latash 2010 for other views).

Indeed, variability in performance has been a strong point in the literature of motor learning. For instance, the Tolerance, Noise, and Covariation (TNC) approach (see Müller and Sternad 2004; Cohen and Sternad 2009) has been categorical in stating that learning is about change to regions of the perceptual-motor workspace where "variability matter less" (Sternad et al., 2014; Sternad, 2018). This has led to a number of experiments on which imposing variability to individuals' performance led individuals to better results in practice (Chu et al., 2013; Zhang et al., 2018). However, this does not imply that adding variability in practice is sufficient. Studies have demonstrated that, in some cases, variability does not directly relate to flexibility in action (Ranganathan & Newell, 2010), and adding variability might be problematic (Cardis et al., 2018). In theory, variability levels might need to be tuned for specific individuals (Harrison & Stergiou, 2015; Schöllhorn et al., 2009; Stergiou et al., 2006).

Our results, then, corroborate the view that individuals interact with the task space and that instability (increased variability) drives non-local changes. Also, the results show that such processes would occur also in different types of tasks. As discussed, this task is redundant and, thus, required consideration of the task space (beyond movement patterns). Further, and important, this task is discrete; our results, then, generalize processes well established in continuous/cyclical tasks (i.e., Kostrubiec et al., 2012; Schöner et al., 1992; Zanone & Kelso, 1992).

Given the results of the latest model, nevertheless, we cannot disregard a possible effect of movement pattern variability in predicting non-local changes. Despite the fact that the variable was not significant, the lowest BIC model required the inclusion of the variable. This can occur if the movement variability varied its effects per individual (it would appear as a random effect as well) – which did not occur – or its inclusion "controls" some of the variance allowing for other variables to be significant – which seems to be the case. Thus, it seems to be the interaction of the perceptual motor workspace with the task space that matters – not only the resultant performance – that lead to non-local changes in practice. It means that *some* variability in movement pattern might be also favoring non-local changes.

An important aspect to be discussed, however, is the fact that the model for non-local changes at the movement pattern level showed only a small effect size. This is not a concern, nevertheless. First, we need to consider that not all individuals demonstrated the non-local change. Thus, some individuals do not perform other movement patterns despite how variable they are. This can result from individuals that do not present other stable movement patterns in their repertoire and, because of this, refrain to change their movement patterns. Second, performance and movement variability, different from common studies on transitions (e.g., Kelso 1984; Scholz and Kelso 1990), will not automatically decrease after the transition. Additionally, given the large drop of non-local changes that individuals showed over days (50% of the non-local changes occurred on the first day), large variability would not mean non-local changes on later days – which blurs even more the relation.

However, a major reason for this blurred relation between movement pattern changes and variability in the task space is that, in redundant tasks, non-local changes in movement patterns might not be at all necessary. That is, in the same way that variability in the movement pattern does not necessarily reflect changes in performance and, thus, do not need to be acted upon, decreased or variable performance might not lead to decreased stability in movement patterns. When such non-local changes at the movement pattern level occur, other factors might also be at play; for instance, local search achieves values near critical points that decrease stability in movement patterns. Thus, the fact that variability on landing was maintained in all models despite these factors is highly relevant.

Local Changes in Search and Its Relation to Non-Local Changes

Our results on the local changes revealed no structure over time – considering linear trends or autocorrelation. This is quite different from other studies that easily find trends over trials in a given dimension of the task (e.g., Wu et al. 2014; Braun, Mehring, and Wolpert 2010; Pacheco and Newell 2018b). Many of these studies employ either simplified task paradigms with reaching/ aiming or are based on modifications of stable perception-action couplings on which effects vanish after few practices. We believe that differences in task constraints are the main source of such differences (Wulf & Shea, 2002). That is, it is possible that the trial-to-trial inherent variability in the present study is *way* larger than in reaching/ aiming studies. This factor seems to be sufficient to modify trial-to-trial trends as demonstrated in an aiming study that manipulated conditions that induced inherent variability (Pacheco & Newell, 2018a).

Furthermore, these results on the autocorrelation were expected. When performing the autocorrelation analyses, we considered sections of trials with *at least* 10 trials but were much larger than that (the average number of trials were of 27 trials with some sections lasting all 210 trials of the day). It means that we were considering a single autocorrelation value for long periods of practice. This is somewhat contradictory as we expected changes within sections to occur *to predict* non-local changes. That is, we used a single autocorrelation value to describe the whole section while expecting for different dynamics within sections. New tools are required to explore local search as, currently, most of them assume stationarity (e.g., Cusumano, Mahoney, and Dingwell 2014; Cusumano and Cesari 2006) and this is clearly not what would be happening in a learning study.

Considering that changes within a section – increased variability during local search – are to predict non-local change, we must deal with an important question: what are the changes that occur within a section that leads to decreased performance, decreased stability or any other changes in practice? We believe that the search for more appropriate informational variables and small modifications in movement aspects might affect stability of the movement patterns but also might change the capability of the individual to maintain stability in his performance. This increases the “range of contact” with the region on which the learner is in the task space (his variability increases) and this might be sufficient to further decrease the stability of the given region of the perceptual-motor workspace. In fact, the small motion through informational variables/movement aspects with the guiding information from the task space might be enough for the system to not settle into any single solution and when such search is enhanced the system inevitably moves to other regions of the perceptual-motor workspace.

Final Comments

This paper demonstrated how non-local changes during practice are frequent and obey established principles in motor control (see Kelso 1995, 2009) and development (see Thelen et al. 1993; Thelen and Smith 1994) of the dynamical systems perspective to motor behavior. We believe that the current effort shows the potential of SSA to understand skill acquisition. The approach follows nicely the process of repetition without repetition proposed by Bernstein (1967) by looking for overall principles of change without dismissing individual characteristics and specific environmental and tasks constraints. The current results showed that such process of search for movement solutions seem to be an intertwined process of local and non-local (global) changes – in the same vein as Gelfand and Tsetlin (1962) proposed.

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Figure Captions

Figure 1. Schematic of the non-local and local analyses for the release parameters considering two dimensions (v_x and v_y) of the release parameters (left) and landing dimensions (right). Each circle represents a hypothetical trial with the darker circles referring to earlier trials. The dashed black line (left) represents the solution of the task (goal space) while the blue triangle (right) represents the target. (a) To characterize a non-local change in the release parameters, the Euclidean distance between a given trial t to $t + 1$ (double headed arrow) would need to be significantly larger than the distance between the previous trials. (b) The local search "change" was defined as a set of trials in a section (see the Methods) which also demonstrate a linear change in either landing dimensions (exemplified by the black arrow on the right). (c) The local search "maintenance" was defined as a set of trials in a section which does not demonstrate any linear change in either release parameters or landing dimensions. (d) The local search "covariation" was defined as a set of trials in a section which shows no linear change in either landing dimensions but show in the release parameters (exemplified by the black arrow on the left).

Figure 2. Schematic of the variability analysis for the movement pattern. α and θ represent any two joint angles. The analysis was performed on 9 dimensions but we show only two as to facilitate comprehension. (a) Hypothetical trajectories (red) of a given set of trials. The blue square represents a time window of 5% of time. (b) and (c) For each time window, a centroid was defined (blue circle) and the distance of each trial to this dot (exemplified by the double headed arrow) was summed to capture the variability at this time point. (b) and (c) show two hypothetical situations with more or less variability.

Figure 3. Schematic of the analyses relating variability over time and non-local changes at (a) the release parameters level or (b) movement patterns. (a) Considering that a hypothetical individual who performed within a given region of the release parameters space (exemplified in terms of v_x and v_y) for the first 17 trials and then showed a non-local change to another region, we observed the variability in both landing dimensions (l_x and l_y) and the number of hits (hits – green circles, misses – red circles) in blocks of ten trials considering the moment of such non-local change. (b) The same was performed for non-local changes at the movement pattern level (characterized by

changes from one cluster to another – see Methods). Here, we also considered the variability in the movement pattern (exemplified by the pointed red lines around the θ^{o} blue line).

Figure 4. Performance change over blocks and days for each individual (gray lines) and for the group (average). The error bars represent the standard deviation.

Figure 5. Shoulder (blue) and elbow (red) average angle trajectory (flexion/extension) over a normalized trial time for an exemplary participant. The average was calculated over a window of 10 trials. The shaded area represents the standard deviation.

Figure 6. Trial-to-trial values of the six release parameters for an exemplary participant. "p's" represent release positions in the *x* (dark blue), *y* (red), and *z* (yellow) axes and "v's" represent release velocities in the *x* (purple), *y* (green), and *z* (light blue) axes. The black dotted line represents the moment of non-local change given large changes in the v_y and v_z release parameters.

Figure 7. Average autocorrelation (lag 1) values for each participant and day of practice. The left panel shows the autocorrelation values considering the first component derived from the principal component analyses and the right panel shows the values for the second component.

Figure 8. Modelled chance of non-local chance occurrence (*z* axis) as a function of landing position variability (in the medio-lateral direction) (*x* axis) and days (*y* axis).