CHANGES IN MOVEMENT REGULARITY DURING LEARNING OF A NOVEL DISCRETE TASK

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Sample entropy and surrogate methods were employed to investigate changes in regularity of movement profiles during the learning of a novel discrete task under contextual interference conditions by two groups. The contextual interference effect was confirmed. Surrogate methods were used to show the presence of deterministic dynamics in observed data. Trends of decreased and increased movement regularity for groups 1 and 2 respectively were observed. The relative stage of learning and the ability to operate within an acceptable range of variability/complexity may explain these trends. Entropy estimates as a measure of regularity may provide important information about the learning of discrete tasks.

KEY WORDS: contextual interference, entropy, movement variability, surrogate.

INTRODUCTION: A principal outcome of the large body of literature on contextual interference is the improved performance on transfer tests of groups exposed to variable training conditions (Brady, 2004). These groups demonstrate an improved ability to adapt their motor patterns learnt during practice to novel tasks. Adaptability is a key concept in the dynamical systems approach to movement, and variability in movement is critical for the process of adaptation (Bartlett, Wheat, & Robins, 2007), which is contrary to other theories which explain variability as indicative of noise within the neuromuscular system (Newell & Corcos, 1993). Entropy measures are non-linear dynamics tools which quantify the regularity of a signal and are effective in providing insight into the health and function of biological systems producing signals (Lake, Richman, Griffin, & Moorman, 2002). However, as entropy quantifies regularity of signals which can be both stochastic and deterministic, the ability to demonstrate that observed data is not solely the outcome of noisy processes is beneficial in pursuing a dynamical systems investigation of movement variability. This can be achieved by adopting surrogate methods (Small, Nakamura, & Luo, 2007). Contrasting observed signals with surrogates generated from an appropriate method can provide evidence against the explanation of movement variability as noise, adding validity to any pre- and post-intervention comparisons of entropy estimates drawn from a population. Therefore, the purpose of this investigation was to use sample entropy and surrogate methods to investigate the changes in movement regularity/variability across the learning of a novel discrete task under contextual interference conditions. It was hypothesised that those learning in a variable task environment would display improved adaptability to novel tasks and subsequently display an increase in motor signal complexity.

METHODS: Twenty informed, consenting, adult males [22.2 (3.3) years; 179.4 (6.5) cm; 78.1 (9.1) kg] participated in this study, randomised into two groups of ten. A contextual interference design was applied to the learning of an overarm throwing task. Group one and group two learning under invariant and variant task conditions respectively. All throwing tasks were performed with the non-dominant hand aiming at one target projected on a 5m x 3m cloth screen at one of the nine locations indicated in Figure 1. The projection volume was aligned such that the central target (2B) was presented at a height of 2 m. Participants were seated with their frontal plane square to the plane of the target at a distance of 7m with their mid-sagittal plane aligned to the perpendicular plane of the target that intersects the centres of the target 1B, 2B, and 3B. Each participant attended nine sessions (Table 1). Instructions were to remain seated and throw as accurately as possible toward the target centre.

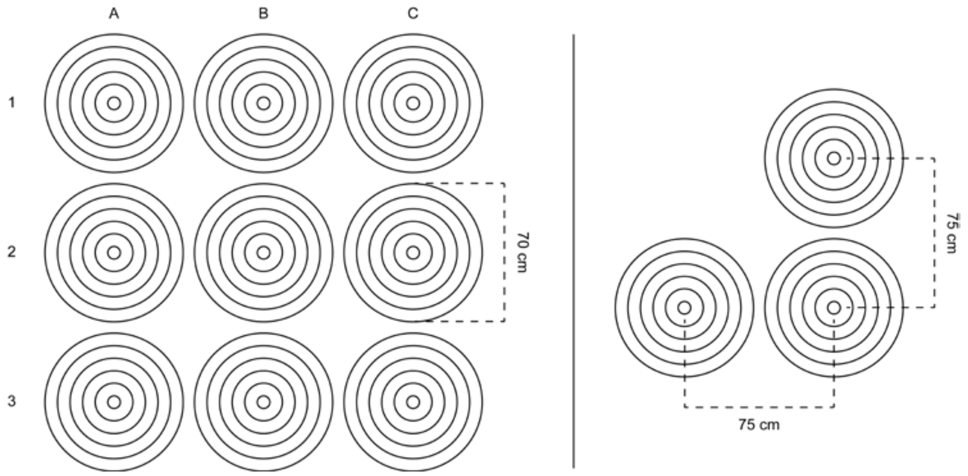

Figure 1: Layout and size of the nine targets used in this investigation (left panel) and separation measurements (right panel). Only one target was visible during each throw.

Table 1
Task flow for sessions 1–9 for each group.

	Group 1	Group 2
Warm up	Self-selected number of throws ~2 mins	Self-selected number of throws ~2 mins
Pre-test	16 throws at target 2B	16 throws at target 2B
Rest	3 minutes	3 minutes
Practice blocks	4 blocks of 10 throws at target 2B (1 min rest between blocks)	4 blocks of 10 randomised throws at targets 1B, 2A, 2C, 3B (1 min rest between blocks)
Rest	3 minutes	3 minutes
Post-test	16 throws at target 2B	16 throws at target 2B
Rest	5 minutes (session 9 only)	5 minutes (session 9 only)
Transfer-Test	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)	4 x 4 throws at randomised novel targets 1A, 1C, 3A, and 3C (session 9 only)

Data collection equipment was predominantly the same as previously reported (Taylor, Lee, Landeo, O'Meara, & Millett, 2015). In addition, a digital video camera (120 Hz) was positioned to collect the moment of impact of the ball with the screen. For this investigation, the data of interest comes from the pre-test of session one, the post-test and transfer-test of session nine. Three dimensional (3-D) marker trajectories were collected for the pre-test and post-test. Three joint rotations were included in these analyses: elbow flexion/extension, shoulder internal/external rotation and wrist flexion/extension.

Throw accuracy was determined by manually digitising the centre of the target and the ball, one frame before impact. Pixel distance between these two points was calculated and divided by the radius of the circle in pixels to create a radial error 'score' such that the lower the score, the more accurate the throw was.

To test for the presence of deterministic dynamics in the observed data, surrogates were generated for each included joint rotation from the pre- and post-tests using a novel method (Taylor et al., 2015). Sample entropy was then estimated for the three time series of each block (3 x 16 concatenated throws) and their respective surrogates (3 x 16 concatenated surrogates).

The dependent variables, radial error score (pre-, post- and transfer-test), surrogate entropy estimates and entropy estimates of the included time series (pre- and post-test) were screened for normality and submitted to appropriate inferential tests. Changes in radial error score (pre- to post-test) within and between groups were analysed using dependent and independent t-tests, respectively. Differences between entropy content of observed data and their respective surrogates were assessed using the Mann Whitney U test. Changes in entropy content of included time series (pre- to post-test) within and between groups were analysed using Wilcoxon Signed Rank and Mann Whitney U tests, respectively. Significance level was set at $p < 0.05$ and appropriate effect size measures were calculated for the parametric and non-parametric statistics (Cohens *d* and *r* respectively where $r = \frac{Z}{\sqrt{N}}$).

RESULTS: Throwing performance of group 1 ($p < 0.05$, $d = 0.73$) and group 2 ($p < 0.01$, $d = 1.44$) significantly improved with practice (Figure 2a). Group 2 also showed significant improvement between pre- and transfer-tests ($p < 0.01$, $d = -0.16$) while the performance of group 1 was not different from pre- to transfer-test (Figure 2a). There was no difference in performance between groups at pre-test ($p = 0.51$, $d = -0.31$), yet group 2 performed significantly better than group 1 in both post- ($p = 0.03$, $d = 0.96$) and transfer-tests ($p < 0.01$, $d = 1.36$).

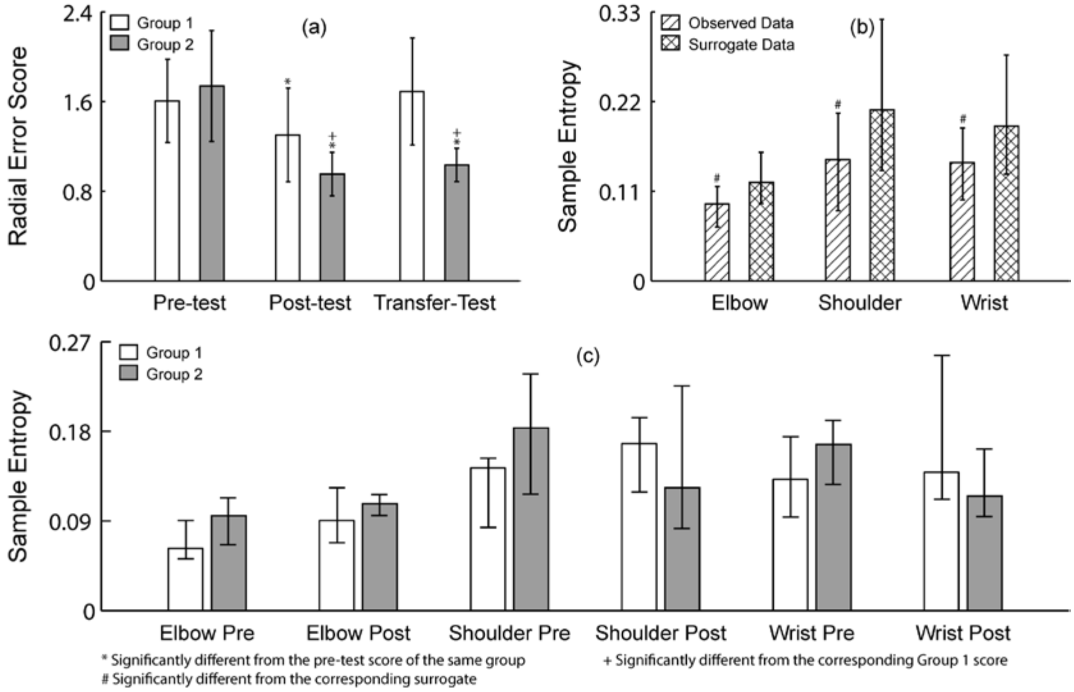

Figure 2: (a) Comparison of mean radial error scores (± *SD*), (b) median entropy estimates (± IQR) for observed and surrogate data (all pairs significantly different $p < 0.01$), (c) median entropy estimates (± IQR) for both groups pre- and post-test.

Sample entropy estimates of observed data were all significantly lower than that of their respective surrogates ($p < 0.01$, $r \leq -0.63$) (Figure 2b). Comparison of entropy estimates, pre- to post-test, within and between groups revealed no significant differences ($p > 0.05$) (Figure 2c). While differences were not significant there was a trend of increasing entropy estimates for group 1 pre- to post-test for elbow, shoulder and wrist with medium, medium and small effect sizes, respectively($r = -0.29$, -0.43, -0.15). Furthermore, there was a decreasing trend (medium effect size, $r \geq 0.33$) in entropy estimate for shoulder and wrist for group 2.

DISCUSSION: The throwing accuracy results confirmed the contextual interference hypothesis as group 2 was superior in performance to group 1 at both post- and transfer-tests. Significantly better performance at the transfer task for group 2 complies with similar results from analogous research designs investigating contextual interference effects (Brady, 2004). The performance of group 2 on the novel transfer task indicates they were better able to adapt movement patterns acquired during practice to new targets.

The results of the entropy comparison of surrogate and observed data suggest that the observed signal contains deterministic information about the neuromuscular system. This indicates that any movement variability identified is a result of neuromuscular control changes. Furthermore, it allows inference to be made when changes are identified in regularity over time, such as the period of learning in this investigation.

The adaptability demonstrated by group 2 may manifest itself as increased movement variability. However, unlike similar work in continuous skills (Preatoni, Ferrario, Dona, Hamill, & Rodano, 2010), no significant differences in regularity were found in the current data. Nevertheless several trends, with medium effects, exist which could lead future research. In particular the trend of regularity decreasing in group 1, while it increased in group 2 is noteworthy. This result goes against the initial hypothesis of this research which had posited that, due to exposure to a variable learning environment, group 2 would acquire and implement a greater range of movement patterns, increasing complexity, during the post-test. It has been suggested that an optimal amount of movement variability exists outside of which outcome consistency is compromised (Button, MacLeod, Sanders, & Coleman, 2003). The throwing accuracy of group 2 may indicate that this group was able to perform within an acceptable bandwidth of variability, remaining adaptable but also consistent in performance. In contrast, group 1 may have been performing beyond this range, which might be due to this group not achieving as advanced a state of learning.

Movement learning can be characterised by three stages: 1) early variability, as an optimal movement solution is sought, 2) constraint of degrees of freedom, a reduction of variability, and 3) freeing of movement degrees and increasing variability, as the mover becomes most proficient (Bernstein, 1967). In the final stage both movement variability and outcome consistency can exist together. It is possible that group 1 was still in an earlier stage of learning such that the greater complexity of their joint time series was actually reflecting the continuing search for an acceptable movement pattern. In contrast, group 2 may have progressed further along the learning continuum, either reducing complexity as they constrained degrees of freedom or, having reduced it, begun increasing it once again. It has been hypothesised that the degree of movement variability over learning/skill level produces a U shaped curve (Wilson, Simpson, van Emmerik, & Hamill, 2008). Applied to this data, the lack of statistical significance could be explained by the groups' displaying similar absolute levels of regularity/variability yet being on opposite sides of the U curve. In order to confirm this, further research is needed to document the session to session changes in regularity as a task is learnt. Once understood, entropy measures may prove a useful tool in tracking and understanding variability during acquisition of skill in both research and applied settings.

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