Action Sequencing, Timing, and Chunking in Space Fortress

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Introduction

Recent cognitive modeling research has been uncovering the complex mechanisms whereby humans learn to combine instruction and experience to acquire rapid and precise complex skills (Anderson *et al.*, 2019). Two key aspects of the learning include the proceduralization of declarative instructions (also known as "production compilation") and the progressive tuning of controllable movement properties to environmental features that predict success in a given task (i.e., internal model; see Anderson *et al.*, 2019).

One promising way of exploring sensorimotor learning during skill acquisition is to look at the details of motor behavior. For instance, it has been shown that motor timing and sequencing variability predicted skill acquisition in a simplified version of the *Space Fortress* (SF) video game (Gianferrara, Betts & Anderson, 2020, 2021). In this project, we focus on action timing and action sequencing in a *SF* video game instantiation with more complex dynamics called *YouTurn* (see Anderson *et al.*, 2019).

In *SF YouTurn*, players are flying a spaceship in a frictionless environment while shooting missiles at a fortress and avoiding shells. To navigate the spaceship, players use four possible keypress actions: "Fire" (F – space bar), "Turn Left" (L – 'A' key), "Turn Right" (R – 'D' key), and "Thrust" (T – 'W' key). To earn points, players accumulate fortress kills over 40 games of 3 minutes. To do so, players need to aim at the fortress and fire a sequence of 10 consecutive shots with intershot intervals of at least 250 ms, and conclude each game cycle with a final quick double shot (with an intershot interval faster than 250 ms). Each fortress kill was rewarded with 100 points, each fired missile cost 2 points, and players lost 100 points for each ship death.

Keypress Chunks over the Games

The notion of motor chunking has been proposed as part of motor skill learning to account for the progressive increase in fluency and accuracy that is usually characteristic of skill acquisition (Diedrichsen & Kornysheva, 2015). Specifically, motor chunks can be thought of in terms of a hierarchical representation of motor skills in which groups of consecutive motor actions are fired collectively as motor units instead of separately as serial actions (Beukema & Verstynen, 2018; Diedrichsen & Kornysheva, 2015). Evidence for motor chunking comes from motor learning experiments, such as the serial reaction time task, in which participants' behavior progressively includes idiosyncratic sequential and temporal groupings, resulting in gradually higher response time autocorrelation at early lags (Verstynen *et al.*, 2012).

We explored the *SF YouTurn* video game dataset from Anderson *et al.* (2019) with $N = 29$ and looked for evidence of action chunking in terms of action sequencing and action timing. Based on past experimental evidence (e.g., Sakai, Kitaguchi & Hikosaka, 2003), we considered that groups of two consecutive keypresses K_1 and K_2 were more likely to be "chunked" when their inter-press interval (IPI) was lower, and when their relative frequency was higher. We thus expressed chunk propensities as follows: $p(chunk_i) = \frac{X\,(chunk_i)}{\sum_k^{n=16} X(chunk_k)}$ where $X(chunk_i) = \frac{Freq\,\%\,(chunk_i)}{IPI(K_1K_2)}$. We computed this propensity for each of the 16 2-keypress chunks over the 40 games.

Figure 1 depicts the progression of each 2-keypress chunk propensity over the 40 games. Figure 2 depicts the average keypress transition probabilities across all 16 chunks. The main result is that as players acquired skills, they tended to preferentially select chunks with a "fire" action while purely navigational chunks became less frequent over the games.

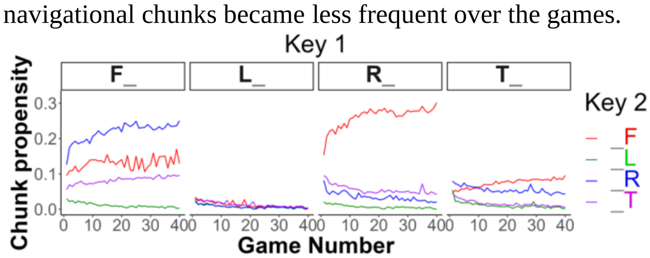

Figure 1: Progression of all 16 2-keypress chunk propensities over the 40 3-min. *SF YouTurn* games.

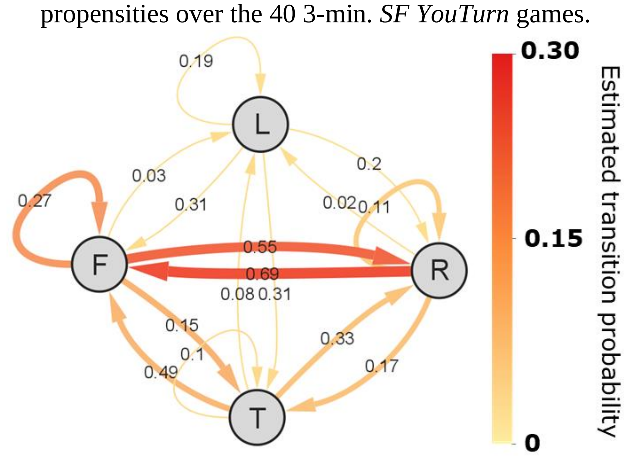

Figure 2: *SF YouTurn* chunk probability network (created in *Cytoscape*[1]). Estimated transition probabilities are shown with edges. Thicker and redder edges are more probable. Edge labels indicate Markov transition probabilities relative to their respective source keypress nodes.

[1]Institute for Systems Biology. (2019). *Cytoscape*. Retrieved from https://www.cytoscape.org

In the context of the *SF YouTurn* video game, shots are particularly important since points are awarded based on participants' ability to pace their "fire" keypress actions. However, the game's frictionless space and speed requirements (i.e., ships get killed if they are too slow) impose additional navigational constraints which must be dealt with simultaneously. The results from Figures 1 and 2 suggest that participants increasingly bound shots with other navigational keypresses as part of action chunks in order to build up skill over the games.

This example of chunking is reminiscent of past incidental learning work on artificial grammars in which participants were asked to remember unfamiliar string sequences, and unintentionally learned strings' environmental statistical regularities (Servan-Schreiber & Anderson, 1990; Perruchet & Pacton, 2006). In such work, chunk formation and hierarchical representational structures were shown to provide an advantage in terms of memory consolidation and recall during learning (Servan-Schreiber & Anderson, 1990). Applied to motor skill learning, a growing body of evidence suggests that elementary movements that are bound into chunks may be retrieved faster and more accurately than individually selected movements (Diedrichsen & Kornysheva, 2015; Beukema & Verstynen, 2018).

Motor Correlates of Skill Acquisition

We next broke down motor skill learning into separate measures of action sequencing and action timing variability. Following the methodology introduced by Gianferrara, Betts & Anderson (2021), we plotted the entropy which measured keypresses' sequential variability in *SF YouTurn*. With 4 keys, there are $4^3 = 64$ keypress triples[2]. The entropy was computed as $H(X) = -\sum_{i=1}^{64} p_i . log_2 p_i$ and ranged from 0 to 6. We also plotted players' action timing variability in terms of the logarithmic coefficient of variation of the inter-shot intervals (ISI) such that $log\ CV(ISI) = log(\sigma(ISI)/\mu(ISI))$ where $\sigma(ISI)$ refers to the standard deviation of the ISIs, and $\mu(ISI)$ refers to their mean. Figure 3 shows the progression of skill in terms of players' performance score (3a), action sequential variability (3b), and shot timing variability (3c).

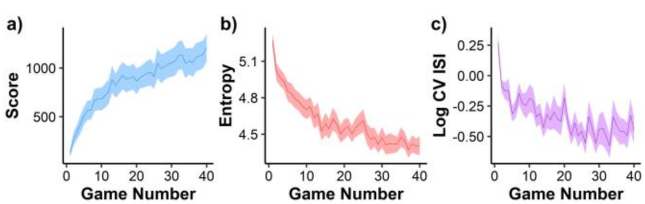

Figure 3: a) Performance over time. b) Action sequencing variability (Entropy) over time. c) Shot timing variability (Log CV ISI) over time. Shaded areas indicate the S.E.M.s.

Note that we filtered out games with no completed game cycles. The current results show data from 1064 individual subjects' games (~92% of all game data).

[2]For purposes of visual illustration, we only represented 2-keypress chunks on Figure 1. We expanded chunks' size to include all keypress triples for entropy computations based on the results from past motor skill learning research (Ariani *et al.*, 2021)

We then averaged each of the three above measures within subjects across all 40 games to investigate inter-individual skill differences (see Figures 4a and 4b). The main result is that lower action sequencing and shot timing variability are correlated with higher scores.

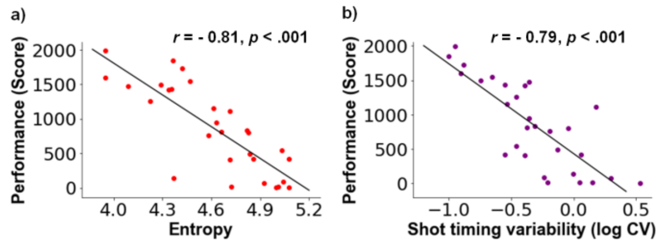

Figure 4: a) Action sequencing variability (Entropy) inter-individual skill differences, b) Shot timing variability (log CV ISI) inter-individual skill differences.

Predicting Skill based on Motor Behavior

Finally, we fit a linear mixed-effects model (LMEM) on game data to assess each measure's ability to predict skill over the games. In R, the model was written as lmer(Score ~ Entropy + logCV + (1|Subject) + (1|GameNb)). Note that 8 observations out of 1064 observations (~ 0.75%) were removed because of model residuals that were more than 3 SDs away from the mean and acted as high-leverage observations. Another model was fit to inter-individual skill data (across games) and was written as lm(Score ~ Entropy + LogCV). Results from both models are shown on Table 1. The main result is that lower measures of action sequencing and shot timing variability significantly predict higher scores across subjects and games.

Table 1: Predicting skill in the *SF YouTurn* video game.

	Skill predictions in YouTurn					
	LMEM across games			*Inter-individual skills*		
	Estimate	95 % CI		Estimate	95 % CI	
Entropy	-560^{***}	(−631,	−492)	-905^{***}	(−1380,	−430)
Log CV ISI	-216^{***}	(−258,	−174)	-765^{***}	(−1181,	−349)
Adjusted R^2		0.87			0.76	

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Conclusion

We showed that our measures of action timing variability and action sequencing variability also predicted skill in a more complex video game closer to the original *Space Fortress* environment. This finding suggests that as players are acquiring skills, they also learn to chunk actions which results in more consistent and fluent motor behavior.

Acknowledgments

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