Simulating Human Periodic Tapping and Implications for Cognitive Models

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Abstract

This project's purpose was to simulate human periodic motor behavior in a simple self-paced tapping task that involved period error correction and feedback processing. When humans try to tap at a certain period, their inter-tap times are normally distributed with a standard deviation that is proportional to the period. When they try to change the period of their tapping, they do so in a single tap instead of a progressive correction taking place over multiple taps. We calibrated ACT-R's new periodic tapping motor extension based on human experimental results and showed that ACT-R can simulate human motor behavior. Future research can leverage these findings and ACT-R's periodic tapping motor extension to simulate fast-paced skilled motor behavior in complex perceptual-motor environments.

Keywords: ACT-R; modeling; motor; period; tapping; error; correction; skill; automaticity

Introduction

Cognitive scientists have recently shown a growing interest in video games and have started to uncover evidence supporting their potential cognitive benefits (Bediou *et al*., 2018). From a psychological standpoint, video games can be useful as a way to investigate complex skill learning processes involving the integration of perceptual, cognitive, and motor information (Anderson *et al*., 2019). In terms of skill acquisition, it is generally acknowledged that skill learning involves a shift from high-level processing of task-related declarative information to the progressive automatization of motor skills (Ackerman, 1988; Anderson, 1982). Acquiring skill in a motor task often involves progressively lower levels of motor variability, potentially due to improved feedback control (Shmuelof, Krakauer & Mazzoni, 2012). In a motor timing video game specifically, skilled behavior was found to be predicted by decreased motor timing variability and increased rhythmicity in motor behavior (Gianferrara, Betts & Anderson, 2020).

Another characteristic of video games is that they often require fast-paced actions which tend to be shorter than a second, and are characterized by more rhythmic motor actions than speeds slower than a second (Gianferrara, Betts & Anderson, 2020). In the brain, actions in the sub-second range are more likely to recruit sub-cortical structures implicated in the motor system such as the basal ganglia and the cerebellum whereas actions in the supra-second range are more likely to recruit cortical structures (Wiener, Turkeltaub & Coslett, 2010). From a modeling perspective, cognitive architectures ought to include suitable motor mechanisms that may account for skilled motor behavior at fast speeds.

We augmented the motor module in the adaptive control of thought rational (ACT-R) architecture with a motor extension to enable ACT-R to engage in rhythmic motor behavior. The starting point for such motor extension is to model human behavior in a self-paced periodic tapping task. Most existing work on periodic tapping has commonly been presented in the context of sensorimotor synchronization studies. Such studies often investigate the process whereby participants first learn to align their taps to a periodic auditory stimulus (synchronization phase) and then continue to tap at that same period (continuation phase; Repp, 2005; Wing, 1980). Though synchronization-continuation paradigms are useful to model periodic tapping and error correction, they often do not provide an account of error correction based on external non-periodic feedback, in which case the adjustment of one's tapping period does not rely on sensorimotor synchronization with a periodic sensory cue.

The goal of this project was to calibrate ACT-R's periodic tapping motor extension based on the human experimental results from a novel game called *ChemLab,* which involves self-paced tapping. In this task, participants learn to adjust their tap frequency based on external feedback that they need to attend to. We first present our results and choice of ACT-R parameterization. We then conclude with some remarks and important implications for future cognitive models.

ChemLab Periodic Tapping Video Game

The goal of *ChemLab* is to fill as many rows of 8 beakers as possible by periodically pressing the space bar. Each beaker's total capacity was set to 100 pixels and each tap within the right tapping interval resulted in an incremental increase of 1/8 of the beaker capacity as well as a brief mid-pitched sine tone (625 Hz). Thus, 8 taps were required to completely fill a beaker. When participants did not press the space bar within the right tapping interval, one out of two possible outcomes could happen: 1) When taps were too fast, a panel with the message "too fast" immediately turned red and a brief high-pitched sine tone (890 Hz) was triggered. Each too-fast tap was penalized by a loss of 5% of the max beaker capacity. The "too fast" light only turned off when taps were at least as slow as the lower (fast) bound of the prescribed tapping interval. 2) When taps were too slow, a panel with the message "too slow" immediately turned blue and a brief low-pitched sine tone (460 Hz) was triggered. Unlike "too fast" feedback, the beaker level progressively decreased at a constant rate of 0.125 % of the beaker's max capacity every 1/60 s. The "too slow" light turned off and the beaker level stopped shrinking when taps became at least as fast as the upper (slow) bound of the tapping interval. An illustration of the *ChemLab* interface is depicted in Figure 1. One can play *ChemLab* by clicking on the following link: http://andersonlab.net/demos/chemlab-v1/

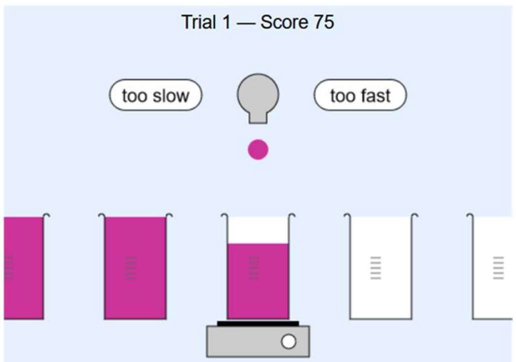

Figure 1: *ChemLab* video game interface.

Experimental Methods

Experimental Design

In this experiment, players completed 9 *ChemLab* sessions of 5 minutes each. In each session, players filled rows of beakers that were selected in a pseudorandom order. Rows of beakers, named trials, belonged to one out of 6 possible conditions that are introduced in Table 1. Each condition included two speeds with two consecutive tapping intervals. The four possible tapping intervals were [200-300 ms], [300-500 ms], [500-800 ms], and [800-1200 ms]. Tapping intervals were non-overlapping and had a range whose width increased at slower speeds. The serial order of trials within sessions was indicated at the top of the screen, along with the score.

Table 1: Description of the 6 *ChemLab* conditions

Condition	Speed 1	Points /beaker	Speed 2	Points /beaker
C1	200-300 ms	10	300-500 ms	20
C2	300-500 ms	20	200-300 ms	10
C3	300-500 ms	20	500-800 ms	30
C4	500-800 ms	30	300-500 ms	20
C5	500-800 ms	30	800-1200 ms	40
C6	800-1200 ms	40	500-800 ms	30

Each trial included 8 beakers that were divided into two phases: the pre-switch phase, and the post-switch phase. Beakers from the pre-switch phase and post-switch phase respectively shared the same tapping interval ("Speed 1" and "Speed 2" in Table 1). When the first post-switch beaker came up the subject would get feedback that they were too fast or too slow and they would have to adjust the period of their tapping accordingly. The transition between the pre-switch and post-switch phases was scheduled pseudo-randomly and could either happen after the completion of 3, 4, or 5 beakers. For each condition, points were earned proportionally to the width and speed of the tapping interval such that slower intervals led to a higher reward than faster intervals. The total reward per trial was computed prior to the start of that trial by computing the sum of points per beaker within each phase (see Table 1) and then adding up the sums from each phase respectively. The total number of points for a trial was then divided by 8 (since there are 8 beakers in each trial), and 1/8 of the total was earned after the completion of each beaker within trials regardless of phase.

Measures

In this experiment, periodic tapping skills were measured in terms of performance within sessions, and in terms of tap variability. One critical *ChemLab* measure related to skill and period error correction was tap feedback.

Performance Score The main way of assessing subjects' *ChemLab* performance was to compute each participant's game score within 5-minute sessions using the scoring system described in Table 1.

Motor Behavior & Tapping Variability We assessed motor behavior by measuring the time between consecutive keypresses' onsets within beakers. This time interval is often referred to as inter-press interval (IPI) in the literature (Diedrichsen & Kornysheva, 2015). Using this measure, it is possible to compute the coefficient of variation (CV), which is the standard deviation divided by the mean of the IPIs. Following previous work on video games, we assessed a logarithmic transformation of CV which measures motor variability and has been shown to be linearly related to performance in a motor timing video game (Gianferrara, Betts & Anderson, 2020).

Finally, we estimated participants' tap regularity levels across speeds by computing the autocorrelation of vectorized tap holds and releases following the methodology from previous work (Gianferrara, Betts & Anderson, 2020). In this computation, keypress holds and releases had a temporal resolution of 1/60 s and we measured the autocorrelation of 100 lags of 1/60 s. We then extracted the correlation coefficient corresponding to the first non-zero positive peak of the autocorrelation function and used this as our tapping regularity estimate.

Tap Feedback In *ChemLab,* skill learning and period error correction mostly happened via the online processing of feedback that followed each individual tap. As mentioned earlier, taps could be categorized as "OK", "too fast", or "too slow". Recording the feedback type that resulted from individual taps is useful because that helps the researcher understand how period error correction happens as a result of exposure to feedback.

Human Participants

A total of thirty-two human participants completed the *ChemLab* experiment. Out of these, one participant was excluded because of poor performance (less than 100 points per session in the last 7 *ChemLab* sessions). A second participant was excluded because their average performance was close to 3 *SDs* below the mean (z = - 2.9; M = 1034 points; SD = 151 points), and their average tap variability level was 4 *SDs* above the mean in terms of the log CV of the IPIs (z = 4.0; M = - 1.35; SD = 0.55).

The 30 remaining participants were aged 22 to 50 years-old (M = 32.8, SD = 7.1). Twenty were male and 10 were female. All participants were recruited on Amazon Mechanical Turk (mTurk). Subjects earned a base pay of \$4 for completing the experiment, in addition to a bonus which was proportional to their performance (in points) as specified in Table 1. On average, participants earned a bonus of \$5.50.

Procedure

To qualify for the experiment, participants needed to correctly answer at least 3 out of 4 multiple choice questions on an English comprehension quiz. The experiment then proceeded as follows: Participants first filled out short background questionnaires. They then read a quick description of *ChemLab* which included instructions on how to proceed. Once ready, participants completed 9 *ChemLab* sessions lasting 5 minutes each. Finally, they filled out some additional questionnaires where they provided feedback and wrote about strategies they found helpful.

Human Results

Behavioral Results

We first present some general results pertaining to human performance and human behavior in the *ChemLab* experiment. Figure 2 provides an illustration of human performance. Figure 2a shows that humans' average game score progressively increased in the 2 first sessions and eventually reached a learning plateau at game 3 onwards when the average game score was consistently greater than 1000 points, which corresponded to more than 90 % of subjects' max performance score in *ChemLab*. Since this study is mostly concerned with skilled motor behavior and the modeling of periodic tapping, we elected to focus on the last 7 sessions at which most of the task-specific skills have been acquired. These included a total of 1014 trials across all subjects and speeds.

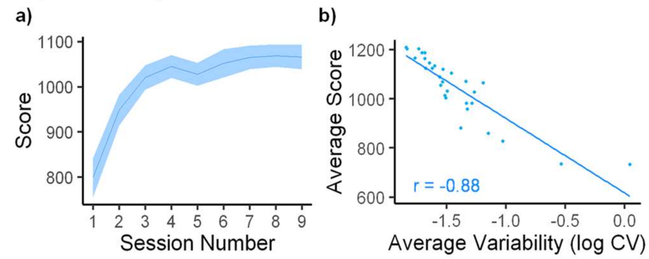

Figure 2: a) Mean game score (performance) over the 9 *ChemLab* sessions. The shaded area indicates the standard error of the means b) Correlation between subjects' average game score across sessions and tap variability as the logarithmic coefficient of variation.

Figure 2b compares individual subjects' performance and motor behavior during the learning plateau (last 7 sessions). Subjects' tap variability is measured in terms of the logarithmic CV and plotted against subjects' average game score across sessions. The main result is that game score is negatively correlated with tap variability (r = - 0.88) meaning that the best performing subjects were also the ones with the lowest levels of tap variability. In terms of motor behavior, tap regularity levels defined with the autocorrelation ranged between r = 0.43 and r = 0.49 across the four different speeds.

With respect to subjects' adaptation to the new tapping period after the switch point, we found that human participants successfully transitioned from speed to speed as can be seen on Figure 3a. Table 2 displays the taps' categories

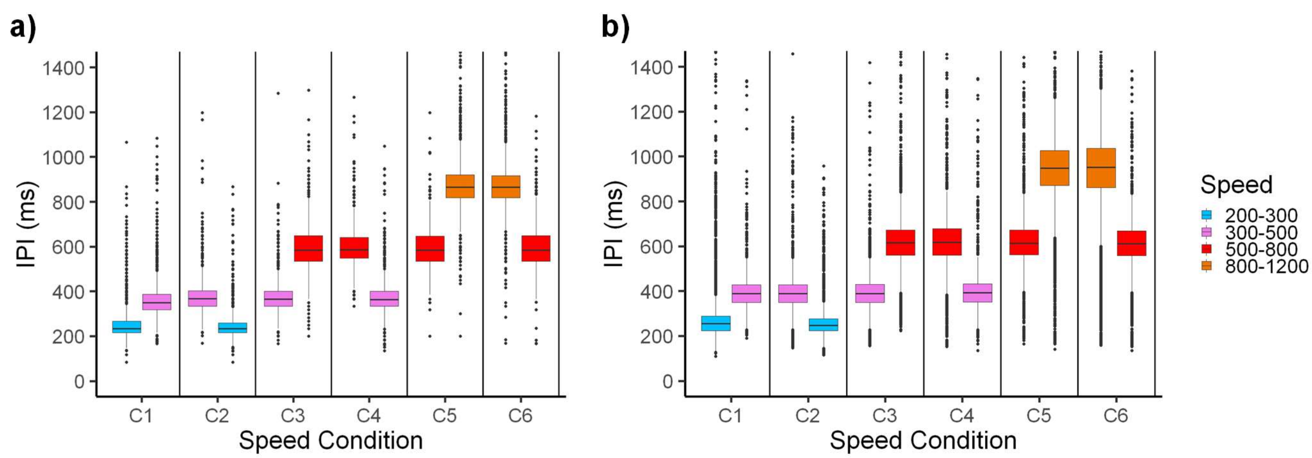

Figure 3: Inter-press interval (IPI) boxplot across the 6 conditions in the pre-switch and post-switch phases. Each speed corresponds to a different color. Human IPIs are depicted to the left (a) and ACT-R model IPIs are depicted to the right (b).

Table 2: Human and ACT-R model tap category proportions across speeds and feedback types.

Feedback	200-300 ms		300-500 ms		500-800 ms		800-1200 ms	
	Humans	*ACT-R*	*Humans*	*ACT-R*	*Humans*	*ACT-R*	*Humans*	*ACT-R*
OK	79.62 %	71.05 %	87.56 %	87.90 %	91.17 %	86.38 %	82.35 %	81.55 %
Fast	10.04 %	11.43 %	8.61 %	7.26 %	7.42 %	9.96 %	16.44 %	14.67 %
Slow	10.36 %	17.52 %	3.83 %	4.85 %	1.41 %	3.67 %	1.21 %	3.79 %

in the assigned tapping interval in the last 2 beakers (stable behavior) of either phase, sorted according to speed and agent (humans vs. ACT-R model). Overall, human subjects executed taps that were in the correct tapping interval ~80% of the time or more.

Feedback Processing

We then investigated participants' response to feedback at the time of the period switch. To reiterate, the tapping interval switched to a consecutive speed bracket after the completion of 3, 4, or 5 beakers (this number was generated pseudorandomly), and players then learned to execute taps at the new speed for the remainder of the trial beakers until they completed the final (8th) beaker.

To explore the process of period error correction, we first computed the proportion of each tap category ("OK", "too fast" and "too slow") for the 8 first IPIs directly following the speed switch. Tap category proportions were computed across all trials from all subjects (see Figure 4). Figure 4's top row illustrates cases in which the speed slowed down, thus resulting in "too fast" feedback, and Figure 4's bottom row illustrates cases in which the speed sped up, thus resulting in "too slow" feedback. Overall, one can see that the majority of participants tended to persevere their taps at the old speed for 1 to 3 taps before adjusting their tap period, though most players needed at least 2 taps before initiating the correction.

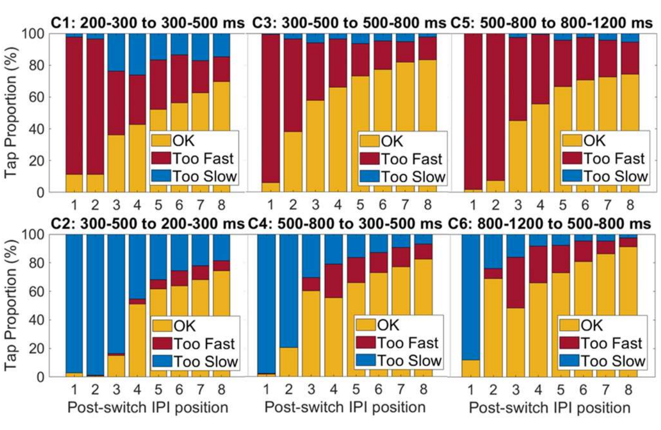

Figure 4: Evolution of tap category proportion as a function of post-switch IPI position following a period switch across the 6 *ChemLab* conditions.

Although Figure 4 suggests that participants may progressively correct their taps' period, we found that this result was due to variation in when the period was corrected and was not indicative of continuous error correction with progressively smaller correcting steps. Instead, we found that period correction happened as a first-order process. Figure 5 shows the difference in IPI as a percentage of the previous IPI at the time of error correction (Pos 0) and at the tap position directly before (Pos -1) and directly after (Pos +1), regardless of the tap serial order in the post-switch beaker.

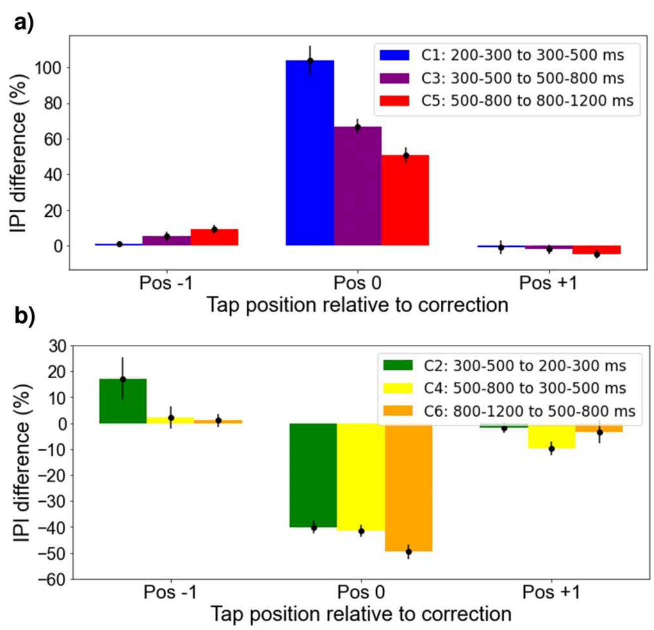

Figure 5: 1st order feedback processing in fast feedback conditions (a) and slow feedback conditions (b). Error bars correspond to the standard error of the means (SEM).

As can be seen on Figure 5, the IPI difference at Pos 0 was greater than at Pos -1 and Pos +1 in conditions in which the tapping interval got slower, but no significant difference relative to no difference (0 %) was found at Pos -1 and Pos +1 (standard deviations at these positions all included 0%). Conversely, the IPI difference at Pos 0 was smaller than at Pos -1 and Pos + 1 in conditions in which the tapping interval got faster, but no significant difference relative to no difference (0 %) was found at Pos -1 and Pos +1.

ACT-R Model of Periodic Tapping

The next step was to integrate into ACT-R a model of tapping and period correction that was consistent with these results. To reiterate, a goal of the project was to use human experimental results in a simple tapping paradigm to calibrate the parameterization of motor parameters in ACT-R.

Periodic Tapping in ACT-R

A motor extension was added to ACT-R, which includes a few basic actions. First, taps can be initiated by making a request to the manual module with information pertaining to the hand, finger, and specific tapping period. Once periodic tapping has been initiated, the manual buffer corresponding to the tapping hand ("manual-right" or "manual-left") continues the tapping action repeatedly. Note that periodic tapping does not require ACT-R to issue specific motor commands for each individual tap, which would not be feasible at the fastest tapping rates. This process is assumed to carry on automatically due to basal ganglia neural activity (Wu, Hallett & Chan, 2015). To stop the period, another request to the manual module can be made in a subsequent production, and ACT-R will then stop periodic tapping once ready. During periodic tapping, upcoming taps are automatically scheduled relative to the previous ones at the time of key release, unless a stop request has been initiated.

The periodic tapping motor extension also includes an additional "tap" buffer which can be accessed to determine the current tap period (in seconds), and a count of the number of taps made at that period. ACT-R can request that the motor module adjust the period at which it is tapping. The "periodic-tap" motor extension code has been created in the Lisp programming language and will be made available to users in an upcoming ACT-R release. We next review parameterization of the periodic tapping motor extension.

ACT-R Periodic Tapping Parameterization

In this paper, we are using the results from the *ChemLab* experiment to calibrate the ACT-R model of periodic tapping. This section is specifically focusing on the choice of noise parameter that governs the variability of taps across speeds. To address the variability in timing between individual taps, we investigated consecutive IPI % differences in an iterative fashion in the last 2 beakers of the pre-switch and post-switch phases. For each beaker, we recorded each tap's IPI % difference relative to the IPI from the previous tap and sorted the IPI % tap differences according to speed. We thus obtained 4 IPI % tap difference frequency distributions which are displayed on Figure 6. As can be seen, the motor noise distribution is centered around 0 % and is normally distributed. One crucial finding was that variability in taps' period across speeds can best be specified in terms of % IPI difference instead of a fixed IPI difference duration, which fits with past sensorimotor synchronization findings (Repp, 2005; Wing, 1980) and may partially be due to fingers' biomechanical constraints (Loehr & Palmer, 2009).

The noise on the tap timing was generated using the same

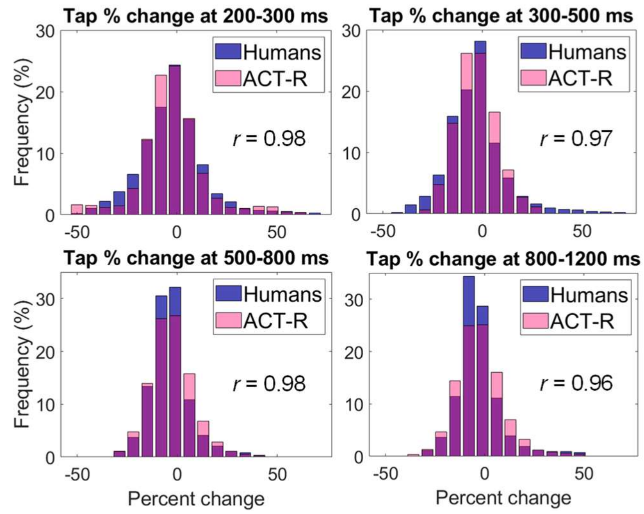

Figure 6: Overlap between human and ACT-R model percent change in tap IPIs. Bins have a width of 7%.

logistic distribution that is used for generating the noise in the ACT-R procedural and declarative systems[1]. The s value of the distribution that best fit the human data was found to be 0.04 (see Figure 6). This corresponds to a standard deviation approximating 7% of the current tap period. The correlation between humans and ACT-R ranged between $r = 0.96$ and $r = 0.98$ across the four speeds.

ACT-R Model of *ChemLab*

Modeling performance in the *ChemLab* experiment not only required us to refine the parameterization of the periodic tapping motor extension in ACT-R, but it also necessitated identifying the key task-specific components of the experimental paradigm that were critical for learning. In this experiment, feedback was the most important experimental feature. Specifically, we needed to create a model that could simulate humans' response to feedback, and error correction.

Responding to Feedback Humans' response to feedback in *ChemLab* was not uniform within subjects as suggested the results displayed in Figure 4. While most period corrections happened shortly after feedback detection and processing, some other corrections happened after a few more taps. In ACT-R, we decomposed this process into three steps represented as separate ACT-R productions: 1) feedback detection, 2) feedback processing, 3) response to feedback.

The first step was to simulate perceptual feedback detection. Our data suggest that there may be perceptual delay and feedback processing differences, which have been hypothesized to be a function of skill level and past exposure to video games (Bediou *et al*., 2018; Bejjanki *et al*., 2014). We used ACT-R's visual-search buffer to model humans' visual detection of color changes that indicated an error, although auditory "too fast" and "too slow" feedbacks

[1] Note that ACT-R uses logistic instead of an actual normal for computational efficiency (Anderson & Lebiere, 1998)

may have played a facilitatory role in feedback detection (Repp & Penel, 2002, 2004). Upon detecting a color change, ACT-R put the interpretation ("too fast" or "too slow") into the imaginal module. To fit human performance, we set the mean time for this action to 50 ms, and the imaginal module adds noise to that from a uniform distribution of +/- 16ms (1/3 of the action duration).

Finally, the last step was to respond to feedback, which was implemented as a first-order process in accordance with the results from Figure 5. Based on our experimental investigation of feedback response, we found that the participants' response to feedback was a probabilistic event which could be simulated with competing productions ("correct" vs. "do-not-correct") and fixed utilities in ACT-R. Utilities were tuned using probabilistic estimates of error correction for fast and slow feedback respectively.

Error Correction Based on the subject data the model responded differently to "too-fast" and "too-slow" feedback. When exposed to "too-fast" feedback, the ACT-R model requested a period error correction from the manual module while maintaining the original tapping rate. When exposed to "too-slow" feedback, however, the model briefly stopped tapping to process the progressively decreasing beaker level caused by the slow taps (see *ChemLab* video game description), and it then made a request for a new tapping period.

The model attempted to correct errors and change the tapping period by adding or subtracting a correction from the period. This correction was expressed as a percentage of the original tapping period and was selected from a gamma distribution[2] generated with a shape parameter k and a scale parameter θ. To fit the subject data, we selected different gamma distributions for each speed.

One striking result was that the gamma distribution underlying "too fast" period corrections was closer to an exponential distribution than the gamma distribution underlying "too slow" corrections. Indeed, k estimates approximated 1 for "too fast" period corrections, regardless of speed (+/- 0.2). For "too slow" corrections, however, k estimates exceeded 2 across all speeds and increased as the tapping rate slowed down. These findings suggest that the shape of the period correction distribution may depend on task-specific feedback features, speed, and potentially feedback saliency.

ACT-R Model Results

We ran two hundred ACT-R model simulations of trials in each of the 6 conditions (1,200 model runs in total). All models were initialized with the same parameters. We then tested whether we could replicate human results from Figure 3a and Table 2. Figure 3b illustrates the model transition from speed to speed in each of the 6 *ChemLab* conditions. To reiterate, IPIs were measured in the last 2 beakers of the pre-switch and post-switch phase, which reflect stable periodic tapping behavior.

We then computed the proportion of tap categories across speeds in either phase and reported these proportions in Table 2 (see ACT-R results). As can be seen, similar tap category proportions were found in ACT-R. A Chi-squared contingency test summarizing within-speeds tap proportion comparisons between ACT-R and humans ($df = 4*2 = 8$) revealed that both proportions were of a similar magnitude ($\chi^2(df = 8, N = 24) = 5.59$, $p = 0.69$).

[2] We utilized the "random-gamma-mt" function from the "cl-randist" Lisp package: http://github.com/lvaruzza/cl-randist/tree/master

Conclusions

The goal of this project was to simulate human motor behavior in a simple self-paced periodic tapping task in which period error correction was driven by visual and auditory feedback. By calibrating our novel periodic tapping motor extension in ACT-R, we showed that it is possible to replicate the general patterns of human behavior and periodic tapping. Some implications are worth noting.

In terms of motor behavior, we found two general mechanisms pertaining to human skill learning. First, we saw that the noise around periodic taps was proportional to the taps' mean and could be simulated as a percentage of the period instead of a fixed time duration, which replicates results from the sensorimotor synchronization literature (Repp, 2005). Second, in the context of the *ChemLab* experiment, we also saw that feedback processing happened as a first-order process akin to reaction time processes.

Because the core periodic tapping code was built as a motor extension in the ACT-R architecture, it is possible for other modelers to use our code as a template of periodic tapping and build upon our work to model human behavior in fast-paced video games involving repetitive motor actions. We look forward to expanding our understanding of skilled motor behavior in complex perceptual-motor environments.

Acknowledgements

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