



Quantifying Behavioral Variability During a Virtual Risk-Taking Task

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Introduction

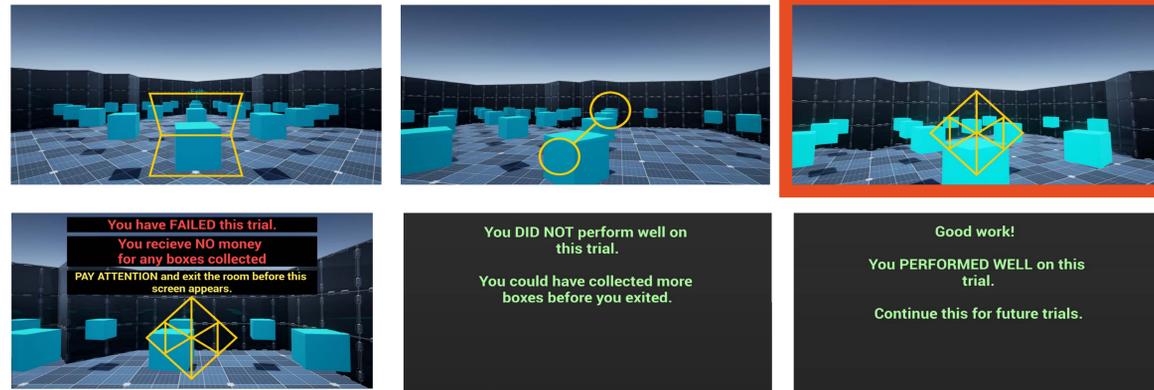
- Behavioral variability is the necessary substrate for the selection of human behavior and behaving variably is functional (Neuringer, 2002).
- Variability can affect the behavioral outcome, the topography of the behavior or both.
- A virtual computer task was built to examine the relationship between outcome success and behavioral (topographical) variability during the task.
- Research Questions**
 - 1) Does behavioral variability predict success?
 - 2) Does behavioral variability change as exposure to the task increases?

Methods

- N= 78 (male)* subjects participated in 60 trials of the virtual task.
- Each trial took $M = 13.2$ s ($SD = 8.7$ s)
- Trials were divided into two sessions and within each session 2 blocks.
- The virtual task is conceptually similar to the Balloon Analogue Risk Task (Lejuez, 2002).
- During each trial subjects were instructed to try to collect as many boxes as possible.
- With each box they collected they earned money (\$0.02/box)
- If they collected too many boxes then the trial would suddenly end and the subjects would not collect any money for the boxes collected on that trial.
- Subjects aggregated collections across trial if they exited the virtual room through the designated exit.
- An arbitrary visual stimulus was displayed on the screen when the probability of trial end was high.
- No instructions were provided before hand regarding the arbitrary visual stimulus.
- Text feedback was provided on the screen after each trial, accumulated earnings were displayed after every other trial.
- Success across trials was measured by the number of trials during a given block in which the subject exited the room with the learned threat stimulus on the screen.
- Player movement variability was classified using Dynamic Time Warping (DTW) is a method to measure the degree of similarity/difference in time series data.

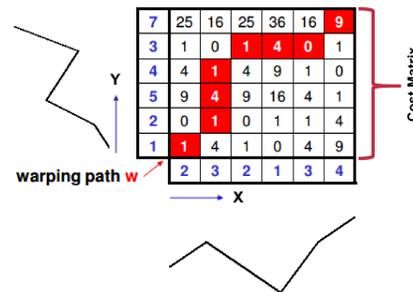
Virtual Risk Taking

Fig 1. Virtual Task Screen Shots



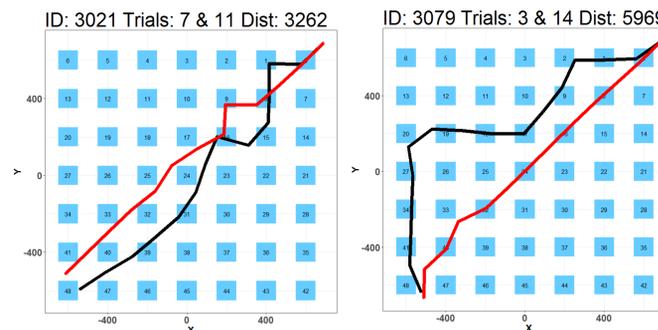
Variability: Dynamic Time Warping (DTW)

Fig 2. DTW Illustrative Example



- Dynamic time warping measures the difference/similarity between two time series data (Sakoe et al. 1978). A cost matrix is initially computed (Fig 2).
- The cost matrix is computed as the squared difference between each observation. A recursive algorithm computes a path that minimizes the difference between all points (warping path; w).
- The sum of this path (red boxes in Fig 2) is the distance.

Fig 3. Representative data of dynamic warping distance of two subjects



- The illustrative example (Fig 3) demonstrates the path of two subjects during two trials (red and black paths).
- A distance index was created for each trial for every subject by taking the mean distance of a trial from all other trials for a given subject.
- Higher scores for a indicate a trial was more different than other trials.

Analysis & Results

- Linear mixed effects models were used for analysis of all statistical models. Analysis were conducted in R version 3.3.1 and utilized *nlme*, *lsmeans*, *dtw*, *plyr* and *ggplot2* packages. All predictors were grand mean centered and diagnostic plots were examined.
- In Tab. 1 and 2 the linear, quadratic and cubic trends were examined across trials for path variation (Distance; DTW) and percent success (aggregated for each block in each session).
- In Tab. 3 Percent success was regressed on DTW distance after controlling for session and block.

Tab 1. DTW trends

	Distance (DTW)
Linear Trend	-152.666* (89.465)
Quadratic Trend	306.932*** (84.601)
Cubic Trend	65.104 (85.873)
Intercept	4,846.295*** (197.381)

Tab 1. % Success trends

	Percent Success
Linear Trend	0.181*** (0.014)
Quadratic Trend	-0.083*** (0.013)
Cubic Trend	0.036*** (0.013)
Intercept	0.736*** (0.018)

Tab 3. % Success on DTW

	Percent Success
Distance (DTW)	0.00003*** (0.00001)
Session (2)	0.243*** (0.023)
Block (2)	0.204*** (0.021)
Session (2):Block (2)	-0.182*** (0.032)
Intercept	0.563*** (0.021)

Note: SE is in parentheses and $p < 0.01 = *$, $p < 0.05 = **$ and $p < 0.01 = ***$

Results

Fig 4. Variation across Trials

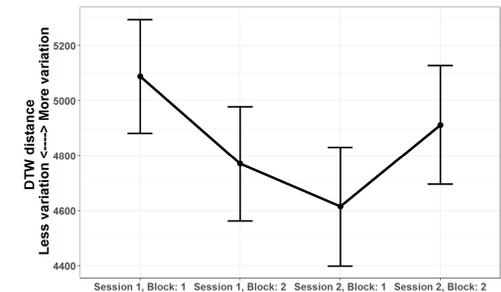


Fig 5. Percent Success across Trials

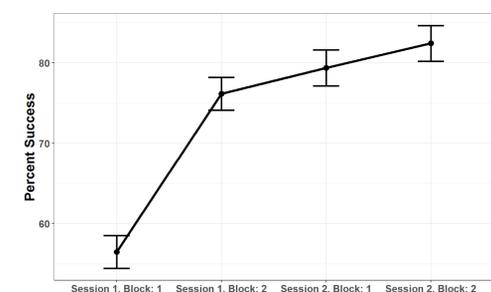
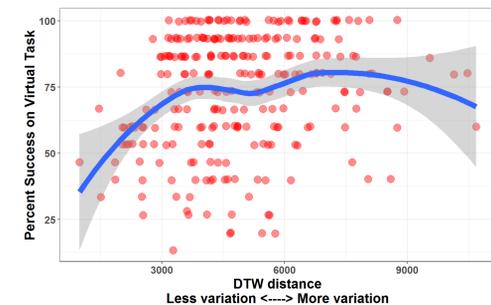


Fig 6. Predicting Success based on variation



Discussion

- Across subjects behavioral variability initially decreases as learning occurs but then increases again towards later trials of the task.
- Despite changes in topographical variability the percentage of trials continues to increase.
- This suggests that learning proceeds with an initial decrease in topographical variability. However, with continued learning topographical variability continues to increase, coinciding with increased success at achieving the desired behavioral outcome.

References

- Neuringer, A. (2002). Operant variability: Evidence, functions, and theory. *Psychonomic Bulletin & Review*, 9(4), 672-705.
- Lejuez, C. W. et al. (2002). Evaluation of a behavioral measure of risk taking: the Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied*, 8(2), 75-84.
- Sakoe, Hiroaki, and Seibi Chiba. "Dynamic programming algorithm optimization for spoken word recognition." *IEEE transactions on acoustics, speech, and signal processing* 26.1 (1978): 43-49.