Using Computer Mouse Tracking for Stress Measurement? An Online Experiment

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Research Synthesis & Big Data Conference
Paper Presentation
Big Data Applications in Psychology
18.05.2021

Table of Contents

Promise of the Measurement Approach

- Computer mouse tracking offers a cheap, convenient and unobtrusive method to gather continous behavioral data [1]
  - utilized in cognitive science to study cognitive processes with a fine-grained temporal resolution [2]

- Potential useful applications of the stress measurement approach:
  - Research method to gather objective stress data when physiological data collection is not possible (e.g. in web-studies)
  - Stress monitoring/manegement tool in settings with frequent computer usage (e.g. office)

Rationale of the Measurement Approach

- Face-validity of an effect of stress on computer mouse usage
- Theoretical considerations and empirical results suggest an interaction between the psychophysiological stress reaction and the sensorimotor activity of computer mouse usage
  - effects of stress on muscle activity [e.g. 3]
  - effects of stress on attentional processes [e.g. 4]
  - Effects of emotional states on computer mouse usage [e.g. 5, 6, 7]
- **However**, the underlying processes are complex and do not allow to postulate hypothesis about a specific effect of stress on mouse usage

Research Question and Goal

Does stress have a recognizable effect on computer mouse usage? Are there meaningful patterns in mouse usage data that hint at the stress level of the user?

Study Overview

- Conducted a between-subject online experiment to test the effect of stress (high-stress vs. low-stress) on mouse usage in four different mouse usage tasks
- Stress manipulation included a threatening vs. neutral framing of the study purpose and a difficult vs. easy stress manipulation task before each mouse task
- Stress assessment via self-report after each mouse task and at the end of the condition
- Participants were recruited via WiSoPanel [8], the final sample was N = 994 (mean age = 54.4, 515 women, 479 men)
- Link to view the study: https://freihaut.github.io/Experiments-Live-Demo/

Manipulation Check

- Compared the self-reported stress ratings after each mouse task and at the end of each condition using mixed ANOVA

☺Small, but consistent differences in the self-reported stress levels on (almost) all rating scales between the high-stress and low-stress condition with higher stress ratings in the high-stress condition

Mouse Data Processing

1. The raw mouse usage data was processed in multiple steps (i.e. artifact removal, interpolation)
2. For each mouse task, we computed a set of features that represent the mouse usage during the task
   - 8 temporal features (e.g. average mouse movement speed)
   - 5 spatial features (e.g. total mouse distance)
   - 4 task specific features (e.g. total distance from an ideal line between two targets)

Data Analysis I

- Compared each mouse usage feature per task between the high-stress and low-stress condition using mixed ANOVA

☹ 1 out of 59 tests showed a significant effect (average mouse movement angle in the slider task) and there was a slight result pattern of increased mouse speed and acceleration across the point-and-click task, drag-and-drop task and slider-task

Data Analysis II

- Used machine learning to predict the experimental condition (classification) from participants mouse usage features
  - 3 algorithms: logistic regression, random forest classification and support vector machine classification
  - Prediction accuracy was assessed with 5-fold cross validation and compared to a null model using a permutation test [9]

☹ In the slider-task, 2 models outperformed random guessing (56% & 59% accuracy). The prediction performance of no other model in no other task was significantly better than random guessing

Data Analysis III

- Used machine learning to predict participants valence and arousal ratings (regression) after each mouse task from their mouse usage features
  - 3 algorithms: linear regression, random forest regression and support vector machine regression
  - R^2 was assessed with 5-fold cross validation (and compared to a null model using a permutation test)

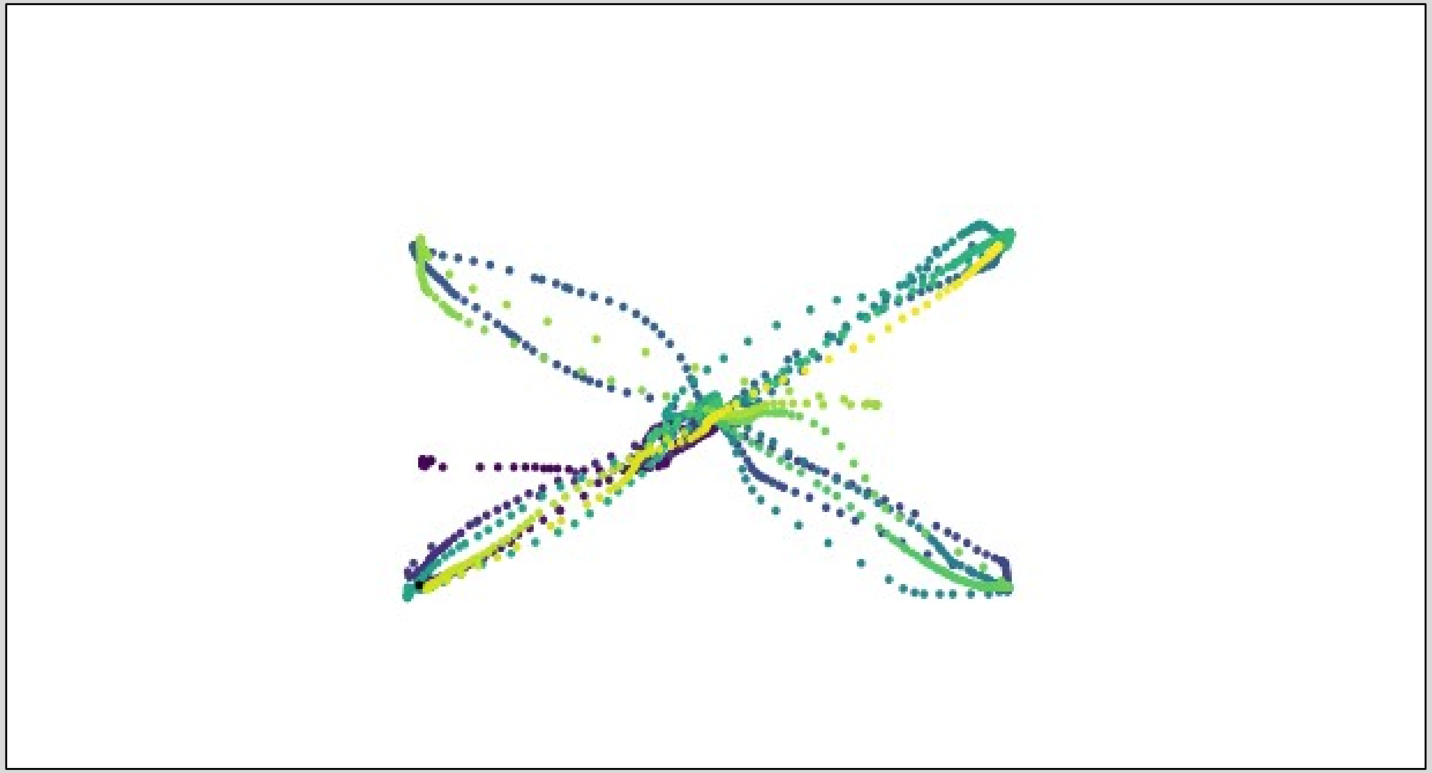
☹ No model predicted valence and arousal with $R^2 > 0$ in any mouse task

Data Analysis IV

- Transforming the raw mouse usage data into single features per task might have caused significant information loss

- We used the raw mouse data (transformed into images) to predict the condition as well as valence and arousal ratings
  - The algorithm was a convolutional neural network (resnet 34)
  - Accuracy and R^2-scores were assessed with a simple random 80%-20% train-test split

Data Analysis IV



☹The approach did not improve any of the predictions

Data Analysis V

- We „validated“ our machine learning classification approaches by testing if the same procedure can be used to classify between different mouse tasks
  - Based on their calculated mouse features
  - Based on the raw mouse usage data (images)

☺The accuracies of both the mouse feature classification approach as well as the image classification approach were 100%

Conclusions

- We found no clear and consistent effects of stress on mouse usage

- Possible interpretations of the results:
  - There is no generalized effect of stress on mouse usage (maybe for isolated mouse tasks?)
  - Interindividual variance in mouse usage and stress reactivity might be too high (use computer mouse tracking for individual stress measurement?)
  - The study had methodological shortcomings that hindered finding an effect
    - Stress manipulation not effective enough
    - Wrong data processing and analysis approach
    - ...
  - There is a lack of knowledge about the micro–level effects of stress

References

Corresponding Research Paper:

Freihaut, P., Göritz, A. S., Rockstroh, C., & Blum, J. (2021). Tracking stress via the computer mouse? Promises and challenges of a potential behavioral stress marker. *Behavior Research Methods*. Advance online publication. https://doi.org/10.3758/s13428-021-01568-8

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