



# Routine Change Detection Using Estimates

Lisa Chudoba<sub>1</sub>, Chance DeSmet<sub>2</sub>, Catherine Sumida<sub>1</sub>, and Taite Winter<sub>3</sub>

Department of Psychology<sub>1</sub>, School of Electrical Engineering and Computer Science<sub>2</sub>, Department of Speech and Hearing Sciences<sub>3</sub>  
Washington State University



## INTRODUCTION

- Programs to promote brain health behaviors have emerged as an important public health initiative.
- Such programs encourage change in behaviors such as physical activity and cognitive engagement.
- Traditional methods of measuring behavior change including self-report, neuropsychological assessments, and physiological measurements have limitations such as unreliability, high cost, and time-burden for both researchers and participants.
- Small, battery-powered binary state-change sensors called Estimates may provide a reliable, unobtrusive, cost-effective, and time-efficient way to measure behavior change in free-living conditions.

## OBJECTIVES

- Determine if estimate data can capture changes in routine after starting a behavior change intervention.
- Examine patterns of routine behaviors between the first three weeks (i.e., week prior to goal setting, cognitive engagement and physical activity goal weeks) and subsequent weeks.

## METHODS

### Study Design

- Participants
  - Selected from a larger intervention
  - Exclusion criteria: a known medical, neurological, or psychiatric cause of cognitive dysfunction.
- Estimate Deployment:
  - Participants interviewed about their daily routine to identify objects that could serve as proxy measures for routine

Figure 1. Participant sample flow diagram

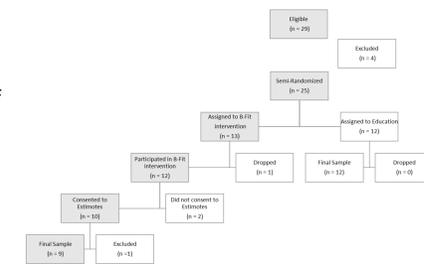
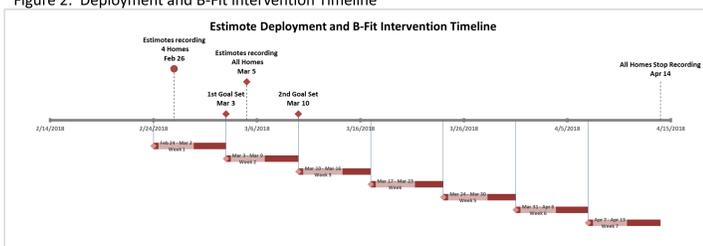


Figure 2: Deployment and B-Fit intervention Timeline



### Hardware and Software

- Estimates
  - Contains accelerometer and temperature sensors
  - Transmits data through radio signals
- iOS App: receives and exports sensor data in a text file
- Data Parsing Application
  - Developed to parse and select data
  - Exported the organized data to a CSV file

Figure 3: Data collection through parsing



- Estimate Inclusion:
  - Estimate stickers selected due to their size and ability to broadcast data via Bluetooth
  - Two types of estimate stickers included—stickers with and without a silicon casing

## DATA

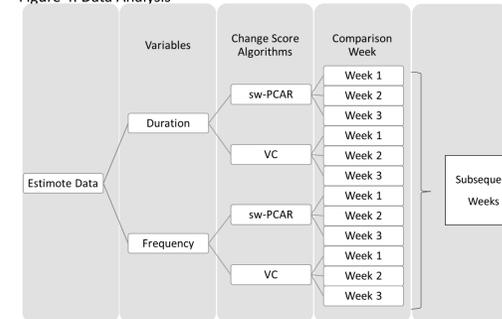
### Pre-Processing

- Selection
  - Only used data from tracking routine (e.g. toilet, sleep, cooking).
  - Duration = the amount of time from the initial “start” time to the next recorded “stop” time.
  - Discrete = amount of times estimates started moving.
- Missing data
  - First day of data collection removed
  - 1 participant removed due to missing data
- Week intervals
  - Data was sectioned off into weekly intervals corresponding to the intervention (see Figure X).
  - First week: missing days were prepadding by simulated days
  - Last week: truncating the end of the dataset

### Data Analysis: Physical Activity Change Detection (PACD; Sprint, 2017)

- PACD used to detect and analyze changes for each house from the estimate data, but modified for weeks.
- Three sets of comparisons with the 1<sup>st</sup>, 2<sup>nd</sup>, & 3<sup>rd</sup> weeks serving as the “baseline” and compared to subsequent weeks.
- Used 2 change scores: permutation-based change detection in activity routine algorithms (sw-PCAR) and virtual classifier (VC).

Figure 4. Data Analysis

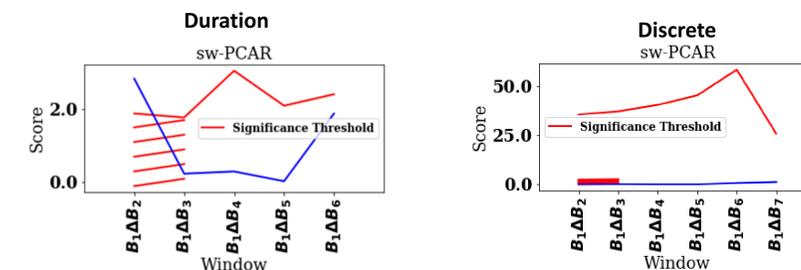


## RESULTS

### Duration vs. Discrete change scores

- Results suggest that there were no similarities between the different weeks.
- Due to missing start or stop signals caused large activity changes in the data.

Figures 5-6. Duration vs. Discrete sw-PCAR results

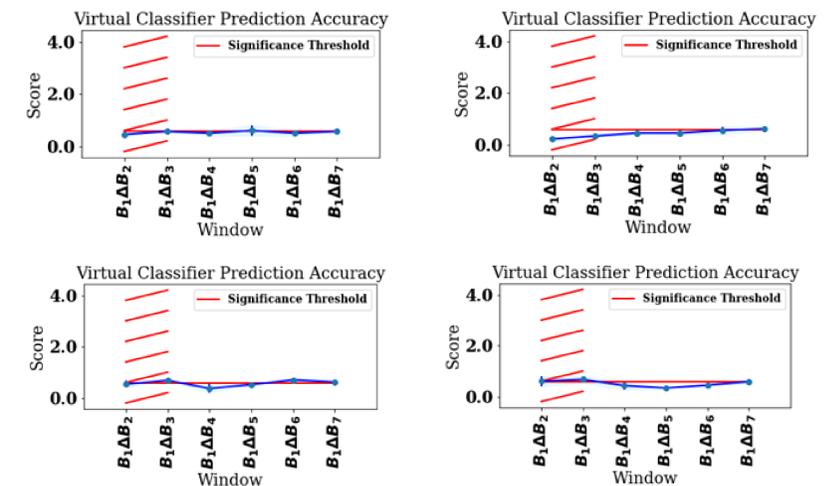


## RESULTS

### Discrete change scores

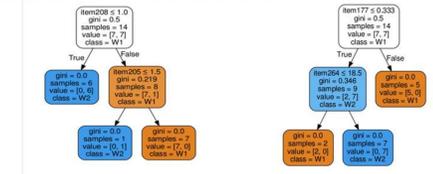
- Change scores more consistent and accurate representations of movement across houses.
- Across homes, there was a change— scores began to rise above the significance threshold.
- Whole this change was slight, there is a definite trend of statistical significance between the 5<sup>th</sup> through 7<sup>th</sup> week.

Figures 7-10. Discrete virtual classifier for four different homes



- Examination of the decision tree demonstrates a reduction in the number of features in a given sensor set.

Figures 11-12. Discrete decision tree for two different homes



## DISCUSSION

- The discrete data is more reliable and can be more effectively parsed for trends in the user’s activities. Although duration data poses some issues, future research could focus on identifying when there are missing “start” and “stop” times.
- Compared to the first week, objects with estimates were moved (i.e., discrete movement) significantly less at the end of the intervention. These results could potentially suggest
  - Estimates made participants more cognizant of moving routine objects at beginning of intervention and then became less aware over time.
  - Intervention initially increased routine activity at beginning of intervention due to new behavior changes, but planning and developed routine improved efficiency of routine behaviors.

### Future directions

- Comparisons may be biased since the study did not monitor routine behavior prior to the intervention starting.
- Therefore, future studies should include a real baseline with more weeks to be compared to long-term health related behavior changes.
- Moreover, since homes varied in size, analyze the accuracy of using estimates to detect routine in multi-person homes.

## REFERENCES

Laditka, J. N., Beard, R. L., Bryant, L. L., Fetterman, D., Hunter, R., Ivey, S., ... Wu, B. (2009). Promoting Cognitive Health: A Formative Research Collaboration of the Healthy Aging Research Network. *The Gerontologist*, 49(5), doi:10.1093/geronl/gbn095

Sprint, G., Cook, D., Fritz, R., and Schmitter-Edgecombe, M. (2016). Using Smart Homes to Detect and Analyze Health Events. *IEEE Computer*, 49(11), 29-37. doi:10.1109/MC.2016.338

Steele, B. G., Bhatt, S., Cain, K., Williams, C., Coughlin, J., & Howard, J. (2003). Bodies in motion: Monitoring daily activity and exercise with motion sensors in people with chronic pulmonary disease. *The Journal of Rehabilitation Research and Development*, 40(5), 45. doi:10.1082/jrd.2003.10.0045

Syha, L. G., Bernstein, E. E., Hubbard, J. L., Keating, L., & Anderson, E. J. (2016). A Practical Guide to Measuring Physical Activity. *Journal of the Academy of Nutrition and Dietetics*, 114(2), 199-208. http://doi.org/10.1016/j.jand.2013.09.018

## SUPPORT

We are grateful for the support and guidance provided by Dr. Cook, Dr. Schmitter-Edgecombe, Dr. Sprint, Dr. Minor and Jason Minor. This work was supported by grants from the National Institute of Biomedical and Bioengineering (R01 EB009675) and the U. S. Department of Education: Graduate Assistance in Areas of National Need (P2004130115)