InterventionViz: A Visual Analysis of Behavior Changing Event Dynamics

T. Murray *Student Member, IEEE*, D. Spruijt-Metz, E. Hekler, A. Raij

Fig. 1. In the Clouds: Vancouver from Cypress Mountain.

Abstract— With the advent of research-grade wearable sensor suites and increasingly ubiquitous human-computer interface comes the opportunity for a new generation of behavioral theory and behavior change methodologies. Just-in-time interventions (JITIs) designed to optimize a subjects behavior based on their momentary context are under exploration as a potentially powerful ally for practitioners and commercial behavior health applications. Analysis of the effect an intervention has on a target behavior is a complex task not well handled by current methods. In this work we introduce novel set of visualization techniques to aid analysis of intervention event effects with emphasis on the dynamics of participant response to intervention. To highlight the strengths and caveats of our techniques, results from data from two trial studies of physical activity interventions and one control dataset are compared.

Index Terms—Radiosity, global illumination, constant time

1 Introduction

TODO: refs are from ubicomp submission

The confluence of pervasive sensing, machine learning, network access, and computation is facilitating new approaches to improving behavioral choices. These systems can detect behaviors and psychological states such as stress[11, 42], physical activity[39, 18], social interaction[62], and smoking[53], automatically and, in some cases, in real-time. These data provide new opportunities for the human-computer interaction (HCI), behavioral science, and other related communities to develop user interfaces for mobile behavioral interventions that help users make better in the moment behavioral choices related to health[36, 46], productivity[29, 56, 31], personal finance[23], and environmental stewardship.[17] New methods for evaluating these behavioral interventions remain underexplored and conventional methods of analysis do not offer the level of detail needed to explore the implicit dynamics of just-in-time, interactive, or adaptive interventions.

Current theories of behavior appear inadequate to inform state-of-the-art intervention development /citeRiley2011, but current methods of intervention analysis are limited in their ability to inform the development of state-of-the-art behavioral theories. In addition to metrics of success, behavioral theorists need tools to help understand the dynamics of behavioral responses to a stimulus. We present methods for exploring these dynamical responses through data visualization.

1.1 Current Intervention Methods

TODO: EXAMPLES OF JITAI (Just In Time Adaptive Interventions) ANALYSIS and HOW METHODS FALL SHORT

1.2 Related Event-based Time Series Visualization

TODO: INSPIRATION TAKEN FROM EXISTING VIZ WORK

1.3 Example Application: Physical Activity

As an example application to demonstrate the strengths of the proposed visual analytics we analyze two empirical datasets with a minute-level metric of physical activity level and intervention events delivered throughout a period of ¿8 days. In both studies interventions were delivered with the intent of increasing subjects physical activity, and responses to interventions varied between participants and delivery contexts. In addition to this data, a control dataset with known intervention responses is included for comparison.

1.3.1 mAvatar Study

An alternating treatment design is used to examine subject behavior over a period of 8+ days in order to test the effect size of an avatar-based live wallpaper deployed on Android phones. Subjects (n=11) aged 11-14 were exposed to a simple, animated cartoon avatar on their mobile device showing alternating levels of physical activity. Each

- *T. Murray is with the University of South Florida. E-mail: tylarmurray@mail.usf.edu.*
- *D. Spruijt-Metz is with .*
- *E. Hekler is with .*
- *A. Raij is with the University of South Florida.*

day the avatar would either be active (playing basketball, running, bicycling) or sedentary (watching TV, on a computer, or playing video games). Fitbit One electronic pedometers were used to estimate subject levels of physical activity via step count.

1.3.2 KnowMe Study

In this study ten teenagers were asked to carry a smartphone and wear an accelerometer and a heart rate monitor (PAdevice??) for 3 days. Physical activity was measured continuously and was monitored in real time. When a subject had been continuously sedentary for two hours, a personalized SMS text message was sent to their phone. Each text message is manually crafted to prompt the subject to be more physically active.

MORE DETAILS NEEDED

1.3.3 Control Dataset

The control dataset is the result of manual recording of one subject undergoing an imaginary, very potent intervention. Whenever the subject was at his desk a random timer was set for an interval ranging from 10 to 120 minutes. When the timer went off, the time was logged and the subject intentionally increased his level of physical activity for a period of no less than 5 minutes. Step counts were recorded throughout the duration of the two-week study period using a fitbit one electronic pedometer.

2 Design

Existing macro-scale methods can determine if an intervention has a significant influence over our target behavior, but it does not give much insight into how the event has an effect over time. The dynamic response to the intervention has only recently become available for study thanks to increasingly ubiquitous wearable sensor technology, and so conventional methods have dealt with low-frequency outcome measures with clever study design. Now that we can measure outcomes at much higher frequencies, methods which leverage this additional information should be adopted.

The dynamic response of the targeted behavior leading up to and following the event tells us much more about how this effect begins and fades over time. A deeper look into the shape of the signal following our event may even reveal a significant effect overlooked by our previous analysis, and much more quantitative behavioral models become possible.

2.1 Highlighting Event Dynamics

The dynamics surrounding a particular event are most commonly shown using a time series. The instance or span of the event is marked on the time-axis and the value of the behavioral measure (physical activity in this case) is encoded in the height at each point in time. We can describe several idealized intervention types based on behavioral theory using this common visualization paradigm.

2 shows the case where an event instantaneously causes permanent change in the target behavior, but in the many cases the intervention will have a temporary effect on the target behavior and will have some delay before setting in.

These intervention response dynamics as shown in 3 are critically important for just-in-time adaptive intervention developers, but are largely unaddressed in current theory.

2.2 Event-time Alignment

time-shifting data view so event is at t=0

2.3 Stacking

stack multiple events to average out noise By analyzing aggregated measurements surrounding each event, we can begin to get a better picture of the latency and delay involved while still averaging out random contextual influences. has same effect as showing average, but individual events still visible

use standard deviation and mean on y-axis to give context

stack multiple participants to achieve more general results

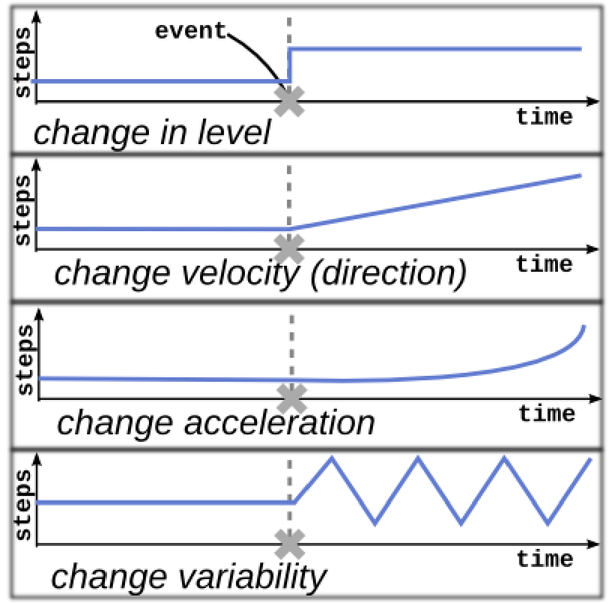

Fig. 2. Theoretical responses to an intervention (adapted from [1]).

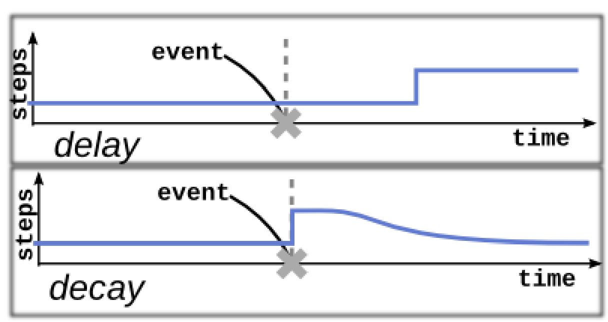

Fig. 3. Level-change responses with delay and decay (adapted from [1]).

2.4 Comparing Event Types

A better analysis is enabled by introducing a control event against which to compare the experimental event. This view presents the average response to our experimental event minus the average control event. This allows us to explore the difference between two events. For example, in the control dataset, intervention events which were not effective at inducing physical activity serve as the control while interventions which were effective serve as the experimental event.

2.5 Dealing With Overlapped Data Frames

When looking at data surrounding an event, we must be cognizant of how instances of the same event at another time may effect our data. For instance, if our analysis targets the 30min following an event, and the event frequently occurs at 10m intervals, the overlapping signals will create unwanted artifacts.

TODO: show simple example with simple bump looks like periodic decay if another event 10m later occurs frequently.

Figure 47 shows a comparison between data retrieved using the two methods of analysis: no overlap vs overlap ignored. Allowing no overlap between events helps ensure that multiple interventions effects do not skew the data, but ignoring these data can drastically reduce data sample if large times following the event are used. This summary of step counts following an avatar view event (either sedentary or active) gives a baseline to which we can compare active-avatar and sedentary-avatar views.

3 Conclusion

The presented visualization methods allow for more detailed analysis of how a subjects behavior responds to a stimuli over time. These methods, when combined with a computational modeling approach to understanding human behavior may enable behavioral scientists to formulate more accurate and more application-ready theories, leading to more effective behavioral interventions.

Acknowledgments

The authors wish to thank A, B, C. This work was supported in part by a grant from XYZ.

References

[1] G. V. Glass, V. L. Willson, and J. M. Gottman. *Design and analysis of time-series experiments*, volume 197. Colorado Associated University Press Boulder, 1975.