Optimizing Behavioral mHealth Interventions Using Control Systems Engineering: The Control Optimization Trial

Presented by:
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Talk Objectives

• To show how control systems engineering, coupled with system identification and behavior change theories, can lead to decision algorithms for achieving personalized, adaptive, and optimized behavioral interventions.

• Introduce the Control Optimization Trial (COT) as an effective means for achieving these interventions.
Some Caveats

• CAVEAT No. 1: As an engineer, *engineering sensibilities* will feature prominently in the talk.

• CAVEAT No. 2: Approach presented will be *idiographic* (i.e., single-subject) in nature.

• CAVEAT No. 3: The Control Optimization Trial is a concept that remains under development.

Helpful References


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Just Walk “Modeling and More” Team
(NSF IIS-1449751, R01CA244777)

• Left: Eric Hekler (Director, Center for Wireless and Population Health, Qualcomm Center, and UCSD Design Lab; Dept. of Family and Public Health); Right: Just Walk team at ASU campus, 2016.
Health Mom Zone Study (R01 HL119245)

Dr. Danielle Symons Downs
Pennsylvania State University

Dr. Jennifer Savage Williams
Pennsylvania State University

- Danielle Symons Downs (Kinesiology, PI) and
  Jennifer Savage Williams (Nutritional Sciences, co-I).
Need for Personalized and *Perpetually Adapting* Interventions

- Understanding individual differences (across participants and over time) is critically important.
Healthy Mom Zone Study (R01 HL119245, Symons Downs, PI)
Representative Participants - Phase 2

- Red curve/bars represent Institute of Medicine (IOM) guidelines
- Physical activity responses for one (of 10) participants to a text message intervention as a proof-of-concept application of control systems engineering.

- Results show clear dynamic behavior and heterogeneity of response.
**Outcome: Cigs Smoked**

- Participant A, Active Drug with Counseling
- Participant B, Placebo with No Counseling

**Mediator: Craving**

- Participant “A” from drug group (blue); participant “B” from placebo group (red)
Common Features

- Lagged dynamic behavior showing distinctive characteristics (e.g., integrating, overdamped, inverse response)

- Outcome variables and other important variables can be measured intensively.

- Multiple intervention options and frequent decision points are available.

- Previous theory and evidence are available to guide intervention development (i.e., the question to answer is not “IF” but “HOW”).
Control Systems Engineering

• The field that relies on *dynamical systems models* to develop algorithms for adjusting system variables so that their behavior over time is transformed from *undesirable* to *desirable*.

• Control engineering plays an important part in many everyday life activities. Some examples of control systems engineering:
  - Cruise control and climate control in automobiles,
  - Home heating and cooling,
  - The artificial pancreas for Type-I diabetics,
  - Fly-by-wire systems in high-performance aircraft.

• Many other examples (including success stories and grand challenges) are presented in [http://ieeecss.org/general/impact-control-technology](http://ieeecss.org/general/impact-control-technology).
From “Open-Loop” Operation to “Closed-Loop” Control

- A well-tuned control system will effectively transfer variability from an important system variable to a less important one.

The transfer of variance (as depicted in this diagram) represents one of the major benefits of control systems engineering.
Navigation Autopilot

• Courtesy of Eric Hekler

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Control Engineering Approach

• Development of dynamical models from data via *system identification* (a method that can be informed by behavior change theories).

• Design of decision algorithms/decision “rules” through model-based methodologies such as Model Predictive Control (MPC).
• *Just Walk* is an idiographic mHealth intervention to promote physical activity in sedentary adults based on *control systems engineering*.

• *Just Walk v1* relies on an experimental procedure using *system identification* to build a *dynamical systems model* that helps explain how step goals, rewards, and external factors influence walking.

• *Just Walk v1* is *not* a fully optimized intervention, but represents the first phase of a *control optimization trial (COT)*, which is part of *Just Walk v2*.

• $N = 20$ participants, 90% female, mean age $= 47.25 \pm 6.16$ years, mean BMI $= 33.79 \pm 6.82 \text{ kg/m}^2$. 
The intervention seeks to promote physical activity (e.g., walking/running) among inactive adults by adjusting *daily step goals* and *expected reward points*, with the ultimate goal of reaching 10,000 steps per day (on average) per week.

**Behavioral Outcomes (examples):**
- Self-Efficacy
- Outcome Expectancies

**Environmental context (examples):**
- Busyness,
- Stress,
- Weather,
- Weekday or weekend
Closing the Intervention Loop: *Just Walk*

The Control Optimization Trial (COT)

- A *informative* identification test provides the data needed to estimate a dynamical system model that can predict participant response to changes (in dosage and context).

- *Initiation* and *maintenance* accomplished by a decision algorithm ("controller") that relies on a dynamical model to decide the magnitude and timing of intervention components.
“Zippered” Multisine Inputs used in *Just Walk v1*

Box, Hunter, and Hunter (*Statistics for Experimenters*), “to find out what happens when you change something it is necessary to change it.”

- Goal range: doable (baseline median) to ambitious (2.5x baseline median).
- These are “pseudo-random”, statistically independent signals.
- 16-day cycles implemented, five or six per participant, over approximately 12 weeks.
Estimating Dynamical System Models

- Black-box, “ready-made” prediction-error models (e.g., ARX),

- Mechanistic, semi-physical models based on behavioral theories,
  - Theory of Planned Behavior
  - Social Cognitive Theory
ARX Model Estimation Procedure

- **Data Preprocessing**: The data is preprocessed for missing entries.

- **Discrete-time parametric modeling**: The filtered data is fitted to a multi-input AutoRegressive with eXternal input (ARX-[na nb nk]) parametric model:

\[
y(t) + \ldots + a_{n_a} y(t - n_a) = b_{11} u_1(t - n_k) + \ldots + b_{n_b 1} u_1(t - n_k - n_b + 1) \\
\vdots \\
+ b_{1i} u_i(t - n_k) + \ldots + b_{n_b i} u_i(t - n_k - n_b + 1) \\
\vdots \\
+ b_{1n_u} u_{n_u}(t - n_k) + \ldots + b_{n_b n_u} u_{n_u}(t - n_k - n_b + 1) + e(t)
\]

- **Validation**: Various measures used, among these the Normalized Root Mean Square Error (NRMSE) fit index:

\[
\text{model fit (\%)} = 100 \times \left(1 - \frac{||y(k) - \hat{y}(k)||_2}{||y(k) - \bar{y}||_2}\right) 
\]

(1)

\(y(k)\) is the measured output, \(\hat{y}(k)\) is the simulated output, \(\bar{y}\) is the mean of all measured \(y(k)\) values, and \(|| \cdot ||_2\) indicates a vector 2-norm (\(||x||_2 \defeq \sqrt{x^T x}\)).
Time series plot showing seven selected input sequences (manipulated inputs & measured disturbances), predicted behavior (from an ARX black-box model), actual behavior, model overall fit, and estimation & validation cycles (1\textsuperscript{st}, 2\textsuperscript{nd}, and 5\textsuperscript{th} for estimation; 3\textsuperscript{rd} and 4\textsuperscript{th} for validation).
Individualized ARX models from black-box system identification for three individuals: Goals, Expected Points, and Granted Points models; B: Predicted Busyness; S: Predicted Stress; T: Predicted Typical; W: Weekday-Weekend.

- Participant A shows no model fit improvement beyond a 4-input model including predicted stress (S).
- Participant B displays significant model fits only with the inclusion of the weekday-weekend input signal.
- Participant C shows no model fit improvement beyond the 3-input model (with goals driving the behavior-change).
• Lead behavioral scientists are Danielle Downs (Kinesiology/Obstetrics and Gynecology) and Jen Savage (Nutritional Sciences), Penn State University (1R01HL119245-01);

• Intervention components include dietary and physical activity (PA) education, individualized dietary and PA prescription, active learning, goal setting, and self monitoring (using records and PA monitors).

• The goal is to show the feasibility of an adaptive, time-varying intervention relying on control systems engineering concepts.

• Measures assessed daily, weekly, bi-weekly, or pre- and post-assessment.
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Overall Schematic Representation
for the Adaptive GWG Intervention

TPB ≡ Theory of Planned Behavior

Energy Intake TPB Model

Physical Activity TPB Model

Maternal Energy Balance Model

Intervention Component Dosages

Decision Rules

Δξ_3

y_1

Energy Intake Self Regulation

Δξ_3

ξ_3

ξ_2

ξ_1

Diet

Fat-free Mass (FFM)

Fat Mass (FM)

Total Gestational Weight

TPB ≡ Theory of Planned Behavior

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Any path diagram can be expressed into a corresponding fluid analogy described by a system of differential equations!
The conservation principle (Accumulation = Inflow – Outflow) leads to the following system of differential equations:

\[
\begin{align*}
\tau_1 \frac{d\eta_1}{dt} &= \gamma_{11}\xi_1(t - \theta_1) - \eta_1(t) + \zeta_1(t) \\
\tau_2 \frac{d\eta_2}{dt} &= \gamma_{22}\xi_2(t - \theta_2) - \eta_2(t) + \zeta_2(t) \\
\tau_3 \frac{d\eta_3}{dt} &= \gamma_{33}\xi_3(t - \theta_3) - \eta_3(t) + \zeta_3(t) \\
\tau_4 \frac{d\eta_4}{dt} &= \beta_{41}\eta_1(t - \theta_4) + \beta_{42}\eta_2(t - \theta_5) + \beta_{43}\eta_3(t - \theta_6) - \eta_4(t) + \zeta_4(t) \\
\tau_5 \frac{d\eta_5}{dt} &= \beta_{54}\eta_4(t - \theta_7) + \beta_{53}\eta_3(t - \theta_8) - \eta_5(t) + \zeta_5(t),
\end{align*}
\]

where:
\(\tau_1, \cdots, \tau_5\) are time constants,
\(\eta_1, \cdots, \eta_5\) are the inventories,
\(\xi_1(t) = b_1(t)e_1(t), \xi_2(t) = n_1(t)m_1(t), \xi_3(t) = c_1(t)p_1(t)\),
\(\gamma_{11}, \cdots, \gamma_{33}\) are the inflow resistances,
\(\beta_{41}, \cdots, \beta_{54}\) are the outflow resistances,
\(\theta_1, \cdots, \theta_7\) are time delays and \(\zeta_1, \cdots, \zeta_5\) are disturbances.
Closed Loop Illustration for GWG
Intervention Fluid Analogy (Energy Intake)

Decision Rules

Intervention Delivery Dynamics

Dosages of Intervention Components

Intervention Fluid Analogy

Self-regulator for GWG

Self-regulator for Diet

Dietary Record

Gestational Weight Gain Measurement

Energy Intake - Theory of Planned Behavior

\[ EI-TPB = \text{Energy Intake - Theory of Planned Behavior} \]

PBC = Perceived Behavioral Control

SN = Subjective Norm

ATT = Attitude

Energy Balance:

FM: Fat Mass

FFM: Fat-Free Mass
HMZ TPB-PA Model Results (Phase 2 Participant)

Subjective Norm ($\eta_2$)

Perceived Behavioral Control ($\eta_3$)

Intention ($\eta_4$)

Behavior ($\eta_5$)

Baseline Intervention (base)

Intervention Step-up (up)

Gestational Age (ga)

PA: Physical Activity

PA - Inputs

PA - SN: Fit = 58%

PA - PBC: Fit = 56%

PA - INT: Fit = 68%

PA (kcal): Fit = 82%
SCT describes a behavioral change model in which individuals proactively self-reflect, self-regulate, and self-organize (Bandura, 1989).

Selected SCT components that are generated as a consequence of variation of external or internal stimuli (outputs) are:

- **Self-efficacy** (e.g. perceived confidence in one's ability)
- **Behavioral outcomes** (e.g. weight loss, physical pain)
- **Behavior** (e.g. physical activity, days of abstinence, cigarettes per day).

Selected variables that act as stimuli to promote (or relegate) behavior and other components (inputs) are:

- **Skills training**
- **Observed behavior (vicarious learning)**
- **Environmental context**
- **Internal and external cues** (e.g. triggers to behavior)

SCT Path Diagram
(from fluid analogy, TBM paper)

Fig. 3 | Path diagram of SCT based on fluid analogy in Fig. 1
Relying on inputs determined important from black-box (ARX) modeling, examine a reduced, parsimonious SCT structure.
Controller Functional Requirements

The decision algorithm/“controller” must:

- consider multiple outcomes,
- decide on multiple intervention dosages,
- incorporate both feedback and feedforward decision-making,
- incorporate constraint handling,
- manage categorical (i.e., discrete-valued) dosages.
Model Predictive Control (MPC) Conceptual Representation

\[
\min_{\Delta u(t) \ldots \Delta u(t+m-1)} J = \sum_{i=1}^{p} Q_e(i)(\hat{y}(t+i) - r(t+i))^2 + \sum_{i=1}^{m} Q_{\Delta u}(i)(\Delta u(t+i-1))^2
\]

- Take Tailoring Variables to Goal
- Penalize Changes in the Intervention Dosages
Conceptual representation of the closed-loop adaptive intervention, based on the simplified version of the SCT model; shows a subset of the measured/designed *Just Walk* signals.

Closed-Loop Intervention (includes Maintenance)

- HMPC algorithm is reconfigured during “maintenance” phases.
Adaptive GWG Intervention: Decision Rule Illustration

- **Time-varying, adaptive** intervention via decision rules involving:
  - augmentation/reduction of components following a certain dosage sequence;
  - at each decision point, only one component can be adjusted.

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**GWG evaluation**

- **Meet GWG goal at study entry, get:** Baseline Intervention
  - Baseline
  - exceed GWG goal at study entry: Step Up

- **GWG evaluation**
  - Meet GWG goal: stay the course (or reduction)
  - exceed GWG goal: Step Up

**assess GWG every couple weeks**

- **Options**
  - Step down 1: reduction of PA component#
  - Step down 2: reduction of HE component*
  - Step down 3: reduction of goal setting

- **Adaptation**
  - Base Dosage for all components
  - Step up 1: 1st augmentation of HE component
  - Step up 2: 2nd augmentation of HE component
  - Step up 3: 1st augmentation of PA component
  - Step up 4: 2nd augmentation of PA component
  - Step up 5: 3rd augmentation of PA component

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• MPC algorithm anticipates the need for dosage augmentations, because of its improved understanding of participant response as a result of the dynamical system model.
In the open-loop portion of the COT, augmentations in HE and PA active learning provide data from which a dynamical system model is obtained.
COT Future Plans

- The COT will be evaluated experimentally in Just Walk v2, which is being developed in fulfillment of the aims of R01CA244777.

- Clinical trial with $N = 386$ is planned; a myriad of activities (involving tech development, measurement, model development, clinical trails, recruitment and meaningful consent) are involved.

- An iterative, intelligent triangulation process is needed to achieve success.
How does this relate to machine learning?

• Machine learning is a very broad field, associated with many tasks beyond decision rules (e.g., classification, detection, etc.)

• Reinforcement learning is probably the closest parallel to control systems engineering; no “hostilities” exist between fields, just different perspectives and points of view.

• Benefits afforded in control systems engineering through:
  • use of behavioral theory to help define model structure.
  • experimental design (using multisines or step changes) to improve model accuracy and reliability.
  • controller robustness (through tuning) means that models need not be perfect to meet requirements.
Summary and Concluding Thoughts

• mHealth behavioral interventions represent an interesting (though challenging) class of control engineering applications, with significant impact on public health.

• Control systems engineering informs the design of decision “rules” and model development for optimized adaptive interventions.

• Behavioral theories allow “physics” to be part of the problem. Their use is a distinctive aspect of the control engineering approach.

• Aspirational goal is to establish the control optimization trial (COT) as a reliable means to build “perpetually adaptive” closed-loop mHealth interventions; this is the basis for Just Walk v2.
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Thank you for your attention!

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