Data-Driven Robust Control for a Closed-Loop Artificial Pancreas

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Type 1 diabetes treatment

- Type 1 diabetes (T1D)** is an autoimmune diseases where the body cannot produce enough insulin to regulate **blood glucose (BG)**
- Current treatment consists of an **insulin pump** (continuous infusion) and a **glucose monitor (CGM)**.
- But these do not communicate with each other, with the patient required to manually manage insulin dosing after each meal.**

The Artificial Pancreas (AP)

- The AP aims to automate T1D treatment through control algorithms integrating insulin pump and glucose sensor.
- Fully closed-loop therapy is challenging** since the BG levels to control depend on **disturbances related to the patient's behavior, mainly meals and physical activity**

Our idea

Construct **data-driven models of meal and exercise behavior**, and develop a **robust model-predictive control (MPC)** algorithm able to reject such uncertainties.

Robust artificial pancreas

System design

Construction of uncertainty sets

Bertsimas et al., *Mathematical Programming* (2013): 1-58

Robust MPC

Finds the insulin therapy at time $t, t+1, \dots$ that **minimizes the worst case performance w.r.t. unknown disturbances (bounded by the uncertainty sets)**

$$\min_{u^t, \dots, u^{t+N_e-1}} \max_{d^t, \dots, d^{t+N_p-1}} \sum_{k=1}^{N_p} d(\tilde{x}(t+k)) + \beta \cdot \sum_{k=0}^{N_e-1} (\Delta u^{t+k})^2$$

Performance: combination of **distance from target trajectory** and **step-wise discrepancy of control strategy**

Moving-horizon state estimator

- It uses a model to minimize **distance between predicted and actual measurements**, and **between predicted and estimated states** over a moving window of length N
- It also estimates the **most-likely disturbances**

$$\min_{\delta^{t-N}, \dots, \delta^{t-1}} \chi(t-N), \dots, \chi(t), \mu \cdot \|\chi(t-N) - \hat{x}(t-N)\|^2 + \sum_{k=0}^{N-1} \frac{\|v^{t-k}\|^2}{q^{t-k}}$$

Results

One-meal experiments

We reproduce synthetic scenarios where

- uncertainty sets are accurate w.r.t. random meals
- uncertainty sets are accurate, but meals behave as outliers
- random meals occur with constant delay
- random meal followed by random exercise

Our robust controller keeps BG in range for 78% to 98% of the time

Meal disturbances from CDC NHANES

- We constructed meal disturbance model from data of CDC NHANES database (8600+ records).
- We clustered the data into 10 main groups, for each deriving random meal disturbances and uncertainty sets.

High-carbs intake

	Chance	Carbs (g)	Time of day (h)
Breakfast	100%	40-60	6:00-10:00
Snack 1	50%	5-25	8:00-11:00
Lunch	100%	70-110	11:00-15:00
Snack 2	50%	5-25	15:00-18:00
Dinner	100%	55-75	18:00-22:00
Snack 3	50%	5-15	22:00-00:00