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

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Type 1 diabetes (T1D)

Main types of diabetes

Consequences

Diabetes can lead to complications in many parts of the body and increase the risk of dying prematurely.



T1D therapy



Image from:

https://www.medtronic-diabetes.com.au/pump-therapy/what-isinsulin-pump-therapy

Insulin pump

Delivers <u>bolus insulin</u> (to cover meals) and <u>basal insulin</u> (to cover demand outside meals)

LIMITATIONS

- Pump and CGM don't communicate with each other
- Bolus is manually set by the patient with meal announcements → danger of wrong dosing

Closed-loop control, aka Artificial Pancreas (AP)



Challenges

 \rightarrow CGM is a "derived" measure of BG (noisy and delayed)

 \rightarrow **Disturbances** related to patient behavior

(Meals and Exercise)

Not just medical but also a CPS challenge

Artificial Pancreas, a control problem

OUR SOLUTION: Data-driven robust model predictive control (MPC) for the AP:

- Closed-loop control of **both basal and bolus insulin**
- Handles uncertainty by learning from data
- Accurate state estimation from CGM measurements



Data-driven uncertainty sets

- Learn from data uncertainty sets that capture realizations of random disturbances (meal and exercise)
- Method that provides uncertainty sets with probabilistic guarantees [Bertsimas et al., Mathematical Programming 167(2), 235–292, 2018]:



Insulin control and state estimation, formally

Robust MPC:

- Find the insulin therapy that minimizes the worst case performance w.r.t. unknown disturbances
- Performance: distance of predicted glucose from target + step-wise discrepancy of control strategy

$$\min_{u^{t},...,u^{t+N_{c}-1}} \max_{\mathbf{d}^{t},...,\mathbf{d}^{t+N_{p}-1}} \sum_{k=1}^{N_{p}} d(\tilde{\mathbf{x}}(t+k)) + \beta \cdot \sum_{k=0}^{N_{c}-1} (\Delta u^{t+k})^{2}$$

Moving Horizon Estimator (MHE), "Estimation a la MPC":

- 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 works also as a meal estimator: estimates the most-likely uncertainty parameter values

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

Virtual patient learnt from NHANES database

- We learn patient models from CDC's NHANES

National Health and Nutrition Examination Survey

- Meal data from 8,611 participants
- Data clustered into 10 main groups





Summary

- Data-driven robust MPC approach for insulin therapy
- In-silico evaluation on real and synthetic data
- Towards fully closed-loop diabetes therapy

Ongoing and future work

- Formal synthesis of robust PID controllers [HVC'17] [ICCAD'18, submitted]
- "Human-in-the-loop" control
- Evaluation on real devices and patients