Committed Moving-Horizon Estimation for Meal Detection and Estimation in Type 1 Diabetes

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Meal Detection in the Artificial Pancreas

Meal Detection and Estimation

- The **artificial pancreas** (AP) automates insulin therapy for type 1 diabetes (T1D), using a control algorithm to compute the insulin dose from continuous glucose monitor (CGM) measurements.
- Commercial AP systems require patients to **manually announce** the amount of carbohydrates (CHO) at each meal for the AP to deliver adequate insulin.
- Meal announcements are a burden and can be **dangerous** because they can be incorrect or late.
- Automated **meal detection and estimation** (MDE) have the potential to replace meal announcements to enable **fully closed-loop** insulin therapy.

Challenges

- There is a time delay between CHO ingestion and BG increase. Also, the CGM measures subcutaneous glucose, which is delayed w.r.t. BG. So, MDE needs **look-ahead** (future CGM measurements) to detect the meal.
- The effect of a meal on BG can be prolonged so MDE also needs **history** (past CGM measurements).
- MDE must be **accurate and timely** for effective BG control

Diagram of closed-loop insulin control with meal detection and estimation

Our idea

Develop a model-based MDE method that combines meal estimations from CGM made at multiple time instants, thus achieving both **look-ahead** and **history**, with **guaranteed detection time**.

CMHE-based Meal Detection and Estimation

Moving-Horizon Estimation (MHE)

- MHE uses CGM measurements and a T1D patient model for state estimation, by minimizing the distance between predicted and actual CGM measurements over a moving window of length N .
- At any time t , the t -th MHE instance also estimates the most-likely CHO disturbances at time $t - N$ to $t - 1$, $\delta_{t-N}^t, \dots, \delta_{t-1}^t$.
- With a window of length N , we have N **possible MHE estimations** for the CHO at time t , $\delta_{t-N}^{t+1}, \dots, \delta_{t-1}^{t+N}$, given by the MHE instances at time $t + 1$ to $t + N$.

Which estimation do we commit to?

- Committing only to δ_{t-N}^{t+1} lacks look-ahead.
- Committing only to δ_{t-1}^{t+N} lacks history: a BG increase for a meal that occurred before t can raise a **false alarm**.
- We develop a new method, **Committed MHE (CMHE)**, for combining multiple estimations

Committed Moving-Horizon Estimation (CMHE)

- At time t , CMHE computes the final CHO estimation for time $t - V$, Δ_{t-V} , as a weighted sum of the past V estimations $\delta_{t-V}^{t-V+1}, \dots, \delta_{t-V}^t$.
- V is called **commitment level**, that is, the detection delay.

Illustration of CMHE with window size N and commitment level V

$$\min_{x_{t-N}, \dots, x_t, \delta_{t-N}^t, \dots, \delta_{t-1}^t} \left[\mu \cdot \|x_{t-N} - \hat{x}_{t-N}\|^2 + \sum_{k=1}^N \frac{\|y_{t-k} - h_{t-k}\|^2}{q_{t-k}} + \eta \cdot \sum_{k=1}^{N-V} \|\delta_{t-k}^t - \Delta_{t-k}\|^2 \right]$$

CMHE minimizes the distance between **predicted and actual measurements**, **predicted and estimated states**, and **currently and previously determined meals**

$$\Delta_{t-V} = \frac{\left(\sum_{i=t-V+1}^t (i-t+1)^a \cdot \delta_{t-V}^i \right)}{\sum_{i=t-V+1}^t (i-t+1)^b}$$

CMHE *time-based* weighting strategy (tunable to favour history over look-ahead or vice versa)

Online Detection Algorithm

- It extracts meal onset, duration, and total CHO amount in real time from CMHE estimations.
- It uses an amplitude threshold Δ and an edge detector for detecting onset and end of a meal.

Results

Random Multiple-Meal Experiments

- 10 rounds of 3-day simulation, 30 days in total.
- Large meals and small snacks
- Random meal CHO amount and onset

	breakfast	snack1	lunch	snack2	dinner	snack3
Probability	100%	50%	100%	50%	100%	50%
CHO amount (g)	40-60	5-25	70-110	5-25	55-75	5-15
Time of day (h)	6:00-10:00	8:00-11:00	11:00-15:00	15:00-18:00	18:00-22:00	22:00-00:00
MDE performance						
Onset Deviation (min)	21.97	27.00	15.28	26.42	16.32	25.08
CHO Deviation (g)	51.44	19.45	23.30	20.27	18.93	15.10
Detection rate	100%	100%	100%	100%	100%	66.67%

Characteristics and detection/estimation results of each meal

Our Performance

- At the **optimal operating point** of the detector, we achieve a 95.38% daily detection rate.
- For **large meals**, we have a **100%** detection rate, with an average of 14.9 minutes onset deviation, and **76.6%** CHO amount estimation accuracy.

ROC curves of **CMHE** and **MHE** obtained with different values for the meal amplitude detection threshold.

An example of detection results for a 3-day experiment

- Large meals, which cause rapid and large BG increase, are our main priority.
- We achieve 100% detection rate for all meals but small late-night snacks.
- Detection of small meals requires low detection thresholds, which leads to false alarms.

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