GLUCOSE FORECASTING USING A PHYSIOLOGICAL MODEL AND STATE ESTIMATION

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Objective

- Accurate glucose forecasting algorithms have been proven to be an effective solution for reducing the risk of hypo- and hyperglycaemia events when combined with glucose alarms and/or low-insulin suspension systems.
- Effective glucose forecasting algorithms can be applied to control insulin delivery in automatic systems.
- Daily routine information (e.g. meal intake, insulin injection, physical exercises) of person with diabetes can be included into forecasting algorithms to improve prediction accuracy.
- In this work, we introduce a novel model-based glucose prediction algorithm which uses deconvolution of the continuous glucose monitoring (CGM) signal to estimate some of the model states in order to improve prediction accuracy.

Methods

Physiological Model

- A composite physiological model **[1]** including a minimal model of glucose-insulin dynamics, an insulin absorption model and a meal absorption model, is employed.
- A deconvolution technique **[2]** is employed to estimate the glucose rate of appearance.
- Meal intake, insulin injection and physical activities reported by the subject are considered as inputs of the model.

Physical Activities and Meal Composition

- Changes on insulin sensitivity (S_I) due to physical exercise **[3]** are considered as follows

$$S_I := \begin{cases} KS_I^o, & \text{during physical activities} \\ S_I^o, & \text{during resting} \end{cases}$$

where S_I^0 is the insulin sensitivity in resting condition and K is a constant (e.g. K=3 for an exercise of 60 min at 50% VO2max).

- Meal glucose absorption variations due to different meal composition **[4]** are considered by modifying the glucose absorption time-to-peak (t_{maxG}) as follows

$$t_{maxG} := \begin{cases} t_{maxG}^o - m, & \text{fast absorption} \\ t_{maxG}^o, & \text{medium absorption} \\ t_{maxG}^o + m, & \text{slow absorption} \end{cases}$$

where t_{maxG}^0 is the default time-to-peak of glucose absorption and m is a constant delay (e.g. m=20min for fast absorption meals).

Individualized Parameters

- Three parameters of the composite physiological model (insulin sensitivity (S_I), insulin absorption time-to-peak (t_{maxI}), and glucose absorption time-to-peak (t_{maxG})) are individualized.

Results

- In silico results using the virtual adult population (n=10) of the UVa-Padova simulator over one-week scenario and 30-min forecasting horizon showed superior forecasting accuracy (RMSE) when compared against the LVX algorithm **[5]** (12.27±1.70 mg/dL vs. 16.17±1.88 mg/dL, p<0.001).
- Considering the impacts of the physical activities and meal composition on the physiological model improves the forecasting RMSE (12.27±1.70 mg/dL vs. 14.21 ±2.16 mg/dL, p<0.001).
- Employing the forecasting technique with retrospective clinical data on 10 subjects with diabetes gives a RMSE of 22.88 ±3.96 mg/dL vs. 24.10 ±4.56 mg/dL with the LVX algorithm (p<0.001).

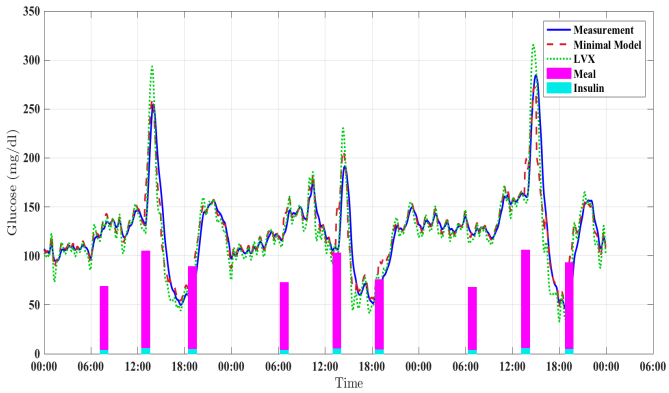

Fig 1. Results for virtual subject adult 1 over a two-day period. Simulated continuous glucose measurements are showed in solid blue line, the prediction results of the LVX method are showed in dotted green line, and the prediction results of the presented method are showed in dashed brown line. Vertical pink bars indicate carbohydrate intakes in grams and vertical light blue bars show insulin boluses in units.

Conclusion

- The proposed forecasting algorithm provides good accuracy and has the potential to reduce hypo- and hyperglycaemia events in a type 1 diabetes population.
- Both in-silico and retrospective clinical data results give superior prediction accuracy when compared with the state of the art LVX algorithm.
- The presented technique is currently being clinically tested as part of a safety layer for an insulin decision support system within the framework of the H2020 PEPPER project.

References

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