Infinite Horizon Prediction of Post Prandial Breakfast Glucose Excursion

Ståhl, Fredrik; Cescon, Marzia; Johansson, Rolf; Renard, Eric

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The objective of the study was to investigate infinite horizon prediction of post prandial blood glucose dynamics after breakfast ingestion using subspace based identification on empirical data.

Data

Five, three days long, patient records (type I diabetes, treated by insulin pump (CSII, n=3) or multiple injections (MDI, n=2)), collected at the Montpellier Clinical Investigation Center within the European DIAdvisor™ project (www.DIAdvisor.eu), were used. The data records contained frequent fingerprick measurements (average 38 samples/day, HemoCue™), continuous glucose monitoring (CGM Abbott Freestyle™) and information on insulin doses and carbohydrate ingestion. The plasma glucose curve was reconstructed from the fingerprick measurements by interpolation. Plasma insulin levels were calculated from the insulin doses using a linear pharmacokinetic model (Wilinska et al. 2005). Using a meal model based upon (Dalla Man et al. 2006) glucose release from the gut following a meal was also assessed.

Model Identification

From these data series an individualized, third order state space model of plasma glucose dynamics was identified for each patient using the subspace-based algorithm N4SID in the Matlab Identification Toolbox. Recent previous attempts on model identification and prediction have been made in (Cescon et al. 2009) and (Stahl & Johansson 2009). The plasma insulin level and gut flux signals, described above, were considered as inputs and the reconstructed plasma glucose curve was used as output. Data from the first night and the following second day breakfast constituted estimation data. The model was cross validated against the first and third breakfasts and compared against the performance of the CGM using Clarke Grid Analysis (pointwise and rate) and RMSE.

Results

Infinite horizon prediction was evaluated for both validation breakfasts for all patients and compared with the performance of the CGM signal in terms of prediction error/measurement error in relation to the reconstructed plasma glucose curve. The infinite horizon predictor outperformed the CGM for all five patients in almost all considered evaluation metrics.

Discussion

Statistical analyses show that the difference in pCGA, rCGA and RMSE between the model prediction and CGM is significant. The performance is generally very good, with no points in zone C, D or E for the pCGA. For the CGA there is one point in zone C. However, this point occurs in the normoglycemic range, and after a short while the model is back on track both in terms of glucose value and direction.

Conclusions

Even though the study is small the results indicate that subspace-based models can be used for prediction of postprandial plasma glucose excursion following breakfasts, with the same accuracy as, or better than, CGM.

Outlook

Further studies will be undertaken on larger data sets to test the methodology in the DIAdvisor™ project within the European FP7-ICT program, IST-216592.

References


Table 1: Performance comparison. Amount of points in zone A in pCGA and rCGA in % and RMSE in mg/dl.

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Figure 1: Data record for patient nr 2.

Figure 2: HemoCue values, model prediction and CGM in val. data for patient 4.

Figure 3: pCGA for model (green) and CGM (blue) for all patients (validation data).

Figure 4: pCGA for model (green) and CGM (blue) for all patients (validation data).