A Novel Meal Detection Algorithm for an Artificial Pancreas

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BACKGROUND

Postprandial glucose fluctuations are a challenge to daytime closed-loop control[1,2] in type 1 diabetes (T1D).

It is predicted that the high number of missed meal boluses experienced during insulin pump therapy[3] will carry over to artificial pancreas therapy.

Therefore, a means to reduce poor outcomes due to unannounced meals must be developed.

The aim of this study is to implement an algorithm to detect meals using data from a continuous glucose monitor (CGM) and the insulin delivered to the subject.

METHODOLOGY

This study utilizes a novel approach to meal detection, which uses a cross-covariance method to detect meals. Similar methods such as, normalized cross-correlation has been used extensively in many image based applications such as object recognition and pattern matching[4].

The meal detection algorithm operates using these following steps:

1. The Unscented Kalman Filter (UKF) utilizes the following equations:
$$x(k+1) = f\big(x(k)\big) + w(k)$$
$$y(k) = g\big(x(k)\big) + v(k)$$
where $x(k)$ is the state vector, $w(k)$ and $v(k)$ are defined to be process and measurement noises respectively. $f(\cdot)$ and $g(\cdot)$ are nonlinear functions.
2. The UKF is employed to predict the states of a composite Bergman-Hovorka model[5] altered to include an auxiliary disturbance parameter, D.
3. An algorithm checks the cross-covariance between D and the CGM values.
4. A threshold is applied to detect an abnormal event.
5. If the threshold is crossed, the forward difference of D is checked at that time point.
6. A positive value indicates a rise in glucose due to a meal.

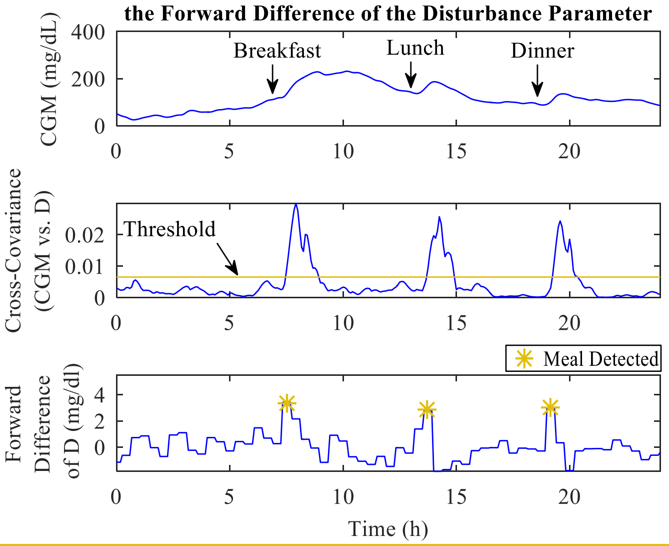
This methodology was evaluated *in silico* using the UVA simulator[6] with 10 adult T1D patients over a period of ten days (30 meals per subject) with insulin sensitivity, circadian and meal variations implemented.

RESULTS

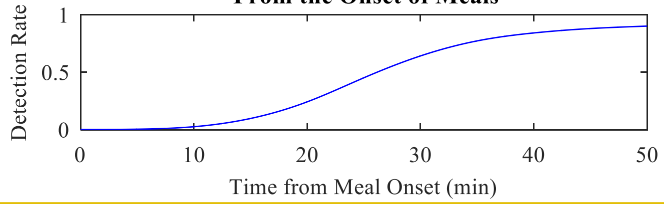
Performance Metrics of the Meal Detection Algorithm

Subject	Specificity (%)	Sensitivity (%)	Accuracy (%)	Δ Glucose (mg/dl)	Detection Time (min)
1	95	97	95	21 ± 10.2	31 ± 8.4
2	93	93	97	14 ± 7.5	24 ± 8.5
3	96	100	97	24 ± 12.8	28 ± 9.4
4	93	100	94	16 ± 11.1	26 ± 8.1
5	99	67	93	24 ± 7.7	31 ± 7.9
6	95	97	95	20 ± 7.4	31 ± 9.9
7	96	67	92	27 ± 7.4	28 ± 6.4
8	94	97	94	15 ± 13.2	31 ± 8.3
9	95	90	94	10 ± 10.1	24 ± 10.6
10	95	93	95	14 ± 8.7	25 ± 7.2
Mean	**95 ± 1.8**	**90 ± 12.7**	**94 ± 1.5**	**19 ± 5.2**	**28 ± 2.8**

Meal Detection Using a Cross-Covariance Threshold and the Forward Difference of the Disturbance Parameter



Cumulative Detection Rates Over Change in Time From the Onset of Meals



DISCUSSION AND CONCLUSION

Results obtained in a very challenging scenario are comparable to other meal detection studies, which achieved sensitivities of 99.6%[7], 95%[8], 94%[9], and 86.9%[10]. One study[9] obtained a lower mean change in glucose of 16 ± 9.42 mg/dl and another[11] obtained a higher mean detection time of 30 min.

In conclusion, we have presented a novel meal detection algorithm that uses information that is readily available, is easy to implement, and is able to detect meals in a timely manner when the change to blood glucose values is minimal. Further work is required to assess its usability in AP applications to mitigate postprandial hyperglycemia due to unannounced meals.

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DPI2013-46982-1-R/2-R, R, Feder Funds

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