A Novel Automated AI Method for Detecting and Classifying CGM Patterns

Shiping Liu[1], Mansur Shomali[2], Abhimanyu Kumbara[2], Kenyon Crowley[1], Michelle Dugas[1], Di Hu[1], Anand K. Iyer[2], Malinda Peeples[2], Guodong (Gordon) Gao[1]

[1]Center for Health Information and Decision Systems, University of Maryland, College Park [2]Welldoc Inc., Columbia, MD

Background and Objectives

- Continuous glucose monitoring (CGM) has emerged as an indispensable tool for helping people with diabetes
- The magnitude and complexity of interpreting the data can be overwhelming for people with diabetes and their clinicians
- Our objective was to develop an automated method to detect and classify discernable, self-management events reflected in CGM data to aid in how the data should be interpreted

Methods

CGM "Event" Detection:

We proposed a computationally-efficient detection algorithm based on time series analysis, and pattern matching. The main steps and applied methods are as follows:

- **Pattern recognition:** We applied dynamic time warping (DTW), hierarchical clustering, and DTW Barycenter averaging to identify the major event patterns (reference patterns in Figure 1).
- **Pattern searching:** The algorithm searches for reference patterns by detecting the encoded sign changes (i.e., positive or negative slope) of the first derivative of the smoothed CGM series.
- **Event attributes extraction:** For each detected event, we extract related information to characterize the event, such as start and end time, start and end status, and severity score.

Training and Testing

- Our algorithm involved two tuning parameters: smoothing degree and slope adjustment threshold. We optimize the parameters by minimizing a modified 0-1 loss function on training data.
- We train for optimal parameters at both the individual and global levels.
- The performance of the algorithm is tested on a separate testing dataset from the same patients.

CGM Event Classification:

For each detected CGM event, we used a three-dimensional characteristics vector, (B,S,E), to label and classify it.

CGM Event Characteristics (B, S, E)

B: glucose status at beginning of a CGM event
S: a calculated severity score defined by time above target and shape of CGM event
E: glucose status at end of a CGM event

Possible levels for B & E:
H (glucose >180 mg/dL)
N (glucose 70-180 mg/dL)
L (glucose 54–70 mg/dL)
VL (glucose <54 mg/dL)

Possible levels for S:
0 (lowest severity) to 9 (highest severity)

Table 1. *Definition Details of CGM Event Characteristics*

Data and Sample

- Our sample data contained 48,121 CGM readings with time stamps for the first 30 days taken from 6 de-identified people with type 1 diabetes
- We split the data into two sets: the first 25 days for training, and the later 5 days for testing

Results

Patient	Training		Testing	
	Number of Events	Error	Number of Events	Error
1	62	80.85 (54)	16	4.33 (14)
2	64	44.95 (53)	12	2.12 (13)
3	64	52.22 (68)	17	46.95 (18)
4	78	40.58 (68)	13	10.15 (11)
5	67	32.32 (58)	19	6.88 (16)
6	59	34.50 (51)	16	9.33 (14)

Table 2. *Performance of the Model*

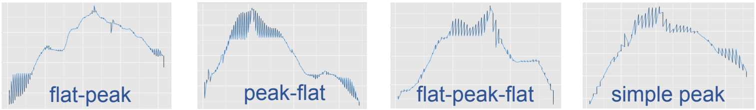

Figure 1. *Four Reference Patterns in the Training Data*

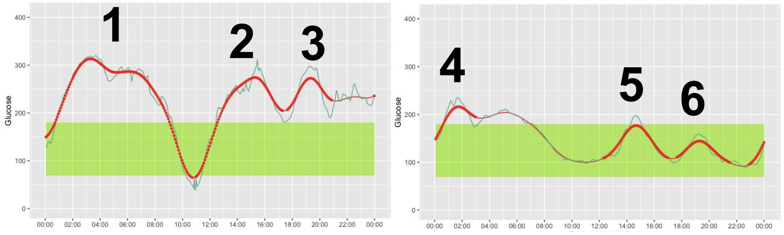

Figure 2: *Example of automated event detection; the thin dark lines shows raw CGM data; thick red lines show events detected by automated system; green zone shows normal glucose target range of 70 to 180 mg/dL*

Event	Start Time	End Time	Start Status	End Status	Score
1	00:00	10:43	N	VL	9
2	10:58	17:17	VL	H	8
3	17:37	20:52	H	H	7
4	23:24	2:59	N	N	4
5	12:19	16:59	N	N	2
6	17:39	21:29	N	N	0

Table 3. *Parameters Associated with CGM Patterns in Figure 2*

Conclusions

- Machine learning and signal detection techniques can be applied to accurately detect CGM events
- The classification of detected events may give CGM users and clinicians more insights into interpreting glucose data, and may be useful in automated coaching of people with diabetes, in remote patient monitoring applications and additionally, for clinical decision support