An Approach for Evaluating and Visualizing CGM Data in People with Diabetes

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

- Traditional methods to manage glucose have historically relied on average-based metrics (e.g., A1c) and have not taken advantage of variability-based metrics (e.g., standard deviation)
- The ambulatory glucose profile (AGP) visualizes and summarizes complex continuous glucose monitor (CGM) data but contains multiple and often difficult to interpret measures
- Our objective was to create a simple visual summary of the data that can provide both average and variability-based insights for CGM users

Data and Sample

- We utilized a CGM data set that contains 4,502,126 glucose measures from 178 individuals with Type 1 diabetes in their first 90 days of activating their CGM devices
- We calculated the following metrics in a daily manner for subsequent analysis and visualization:

ave-G	average glucose in mg/dL
sd-G	standard deviation of glucose in mg/dL
PCV	coefficient of variation in percentage (%)
TIR	% of time in the range between 70-180 mg/dL
TAR	% of time above the range
TBR	% of time below the range

Table 1. *List of CGM Metrics*

Methods

Measure Correlation: We applied within-subject correlation (WSCor) to address the correlations between pairs of metrics with the consideration that each metric was calculated per day for one individual. The WSCor method can capture both within-subject correlations while adjusting the within- and between-subject variations.

Feature Selection: A within-subject principal component analysis (PCA) was deployed to select the *p* most important metrics based on the *p* PCs where the cumulative variation explained by the first *p* PCs is greater than 90%. We selected the metric that contributes the most from each of the *p* PCs.

New Framework: We used the selected metrics to classify glucose status for an individual in a certain period. Moreover, we visualized the status change over time to monitor, report, and utilize the CGM data summary longitudinally.

Results

We found strong correlations between some metrics in Table 2. Measures of mean glucose levels, ave-G, TIR, and TAR, are highly correlated with each other; and measures of glucose variation, sd-G and PCV, are also strongly correlated. Table 2 shows the correlation values and strong correlations are highlighted in bold.

WSCor	ave-G	sd-G	PCV	TIR	TAR
ave-G	1				
sd-G	0.470	1			
PCV	-0.082	**0.819**	1		
TIR	**-0.816**	-0.495	-0.122	1	
TAR	**0.907**	0.430	-0.028	**-0.957**	1
TBR	-0.379	0.179	0.505	-0.065	-0.228

Table 2. *WSCor Matrix for All Metrics*

In the analysis, we identified the metrics that are strongly correlated; our goal was to eliminate redundant information in order to simplify a person's glucose status. Thus, we applied the feature selection procedure based on within-subject analysis.

Figure 1 displays the cumulative "explained variations" for 6 components; the first 3 PCs "explained" more than 90% of variation (red dashed line in top-left plot in Figure 1). Checking the absolute values of coefficients, we selected TIR, PCV, and TBR for PC 1, 2, and 3 respectively.

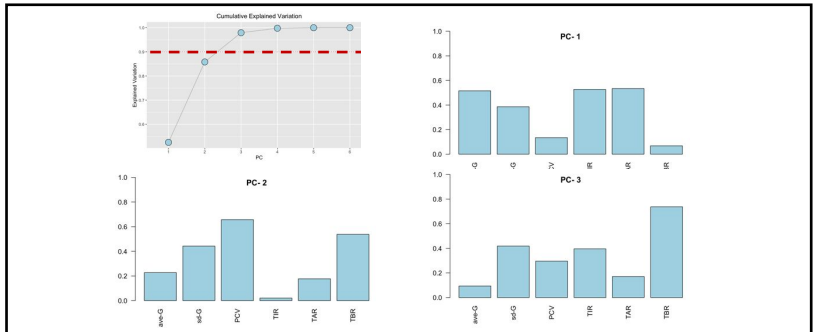

Figure 1. *Cumulative Explained Variation and Coefficient Magnitudes of Major PCs*

Using the selected metrics, we classified patients into different statuses by a 3-dimension measure, (TIR, PCV, TBR). For the first two dimensions, 4 statuses, "G-G", "G-B", "B-G", "B-B", are given where the first and second letter indicate good/bad status in terms of weekly average on daily TIR and PCV with threshold ≥70% and ≤36%, respectively. The third dimension is classified into "TBR" and "Non-TBR" based on a patients' daily TBR >5% for any day of the week.

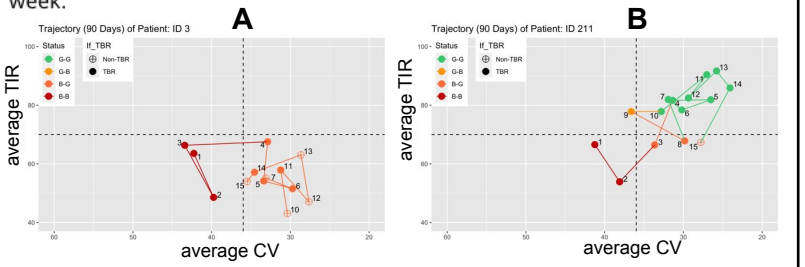

Figure 2. *Two examples of the novel CGM data visualization. The user in A has improved glucose variability and hypoglycemia but TIR remains low. The user in B has reached recommended levels of TIR and glucose variability but has excessive hypoglycemia.*

Conclusions

This novel data visualization based on the key CGM metrics may assist CGM users and their clinicians in assessing overall progress with glucose control over time.