Master Thesis - Project Specification

Meal Detection and Carbohydrate Estimation from Continuous Glucose Monitoring data

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Abstract

About this document...

Diabetes is on the rise... Proper care comes from good data... Diet is of major concern... CGM allows easy data collection... Meal detection is... Carbohydrate estimation...

Contents

Chapter 1

Introduction

This chapter intends to provide the reader with an overview of the current state of diabetes healthcare as well as explain the outline, aim and limitation of this thesis project.

1.1 Project Introduction

In every country the disease burden related to diabetes is already high, and it is steadily increasing [8]. In 2017 the estimated prevalence of diabetes was 451 million people globally and approximately 5 million deaths were attributed to diabetes [3]. Aside from reduced life expectancy, diabetes increase the risk of multiple other conditions such as heart disease, stroke and peripheral vascular diseases [8]. With a projected prevalence of 693 million diabetes patients in 2045 and given the seriousness of diabetes, proper medical care for patients are of utmost importance [3].

Diabetes is a group of metabolic diseases that is characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both [1]. Insulin is necessary to maintain normal blood glucose (BG) levels by facilitating cellular glucose uptake and regulating carbohydrate metabolism [12]. The vast majority of cases of diabetes fall into two broad categories, type 1 diabetes (T1D) or type 2. T1D is caused by an absolute deficiency of insulin secretion, thus patients need to induce exogenous insulin on a regular basis to maintain balanced BG levels [1].

Maintaining balanced BG levels is an every day challenge of T1D patients. Treatment guidelines put heavy emphasis on self management activities that benefits a balanced regulation. This include activities such as eating patterns, exercise and carbohydrate consumption. Patients favorably consults a clinician regularly to get consultation regarding evalation and making plans for the self management process [4].

Continuous glucose monitoring (CGM) sensors are wearable devices that measures the blood glucose frequently (usually every 1-5 minutes). The data CGM sensors provide have revolutionized the ability for clinicians to review a patients data and deliver care driven by consistent data [6]. Care on CGM data have proven effective in lowering patients long term average BG concentration (A1C) [5]. The data provide effictive insigt in immediate processes such as accuracy of a specific insulin dosing, the BG concentration peak of a certain meal etc. However, there is a lack of research in deriving insights for long term medical advice autonomous from CGM data.

1.2 Project Aim

Generating insigt in long term outcomes of a T1D patient's historical data could provide benefits to both patients and clinicians. Patients could receive feedback automated feedback of current habits and its potential impact on long term A1C. Clinicians benefit from automated insights in a patient's be reducing the risk of missing patterns. Autonomous insights can be reviewd by clinicians as second opinion to form a more objective care plan too.

1.2.1 Objective

The objective of this thesis is to investigate how an automonous system, which fulfills the cartain criteria below, can be implemented and in which configuration it perfoms optimally. The system should:

- Detect events in from a batch CGM time series data (such as meal, exercise or sleep).
- Classify the event of the event.
- Estimate intervention caused by an event (what impact did the event have on the continued time series).

1.2.2 Research Question

Can techniques and algorithms X, Y, Z provide a system complying with the specifications defined in Objective?

Chapter 2

Background

This chapter sets out define diabetes and the relevant aspects of T1D care enough to understand the content in latter chapters. It further describes theory of the techniques in the suggested method and reviews related work that should assist putting this thesis into context of the current field.

[This chapter is under construction. It should be continued when the method is decided upon.]

Chapter 3

Method

3.1 Data

The data is collected during a 4,5 month pilot study includes 20 patients. All patients are at least 18 years old and have been injecting insulin at least 1 year prior to the study. Each patient are equipped with a CGM sensor for the entirety of the study. For each patient, the CGM sensor measures the BG concentration (BGC) at intervals of 1-5 minutes. The time-BGC constitues the structure of each patient's data set. Additionally, other events such as meals and exercise are logged manually by and are also associated with a certain time. A summary of collected data points are presented in table 3.1.

Notation	Field	Format
P	Patient	Integer
t	Time	Date
t_{BG}	Glucose value at t	Float
t_{ACT}	Physical activity at t	Integer
t_{INS}	Injected insulin at t	Float
t_{IMG}	Food image at t	Float
t_{EVENT}	Manually reported by patient at t	Text

Table 3.1: The data for each patient include continuous measurements at time steps t of intervals between 1-5 minutes. Each measurement at t *always* include BG value and *may* contain other field presented in the table.

3.2 Implementation

The objective of the proposed system is to analyse the data for a closed time interval, identify meaningful events and classify them accordingly with respect to their influence over future measurements. The analysis is not performed in real time, thus should be considered a batch problem (that is, all data is available immideatly). The proposed steps of implementation can be overviewed in figure 3.1. Each step is described in more detail in its corresponding section below.

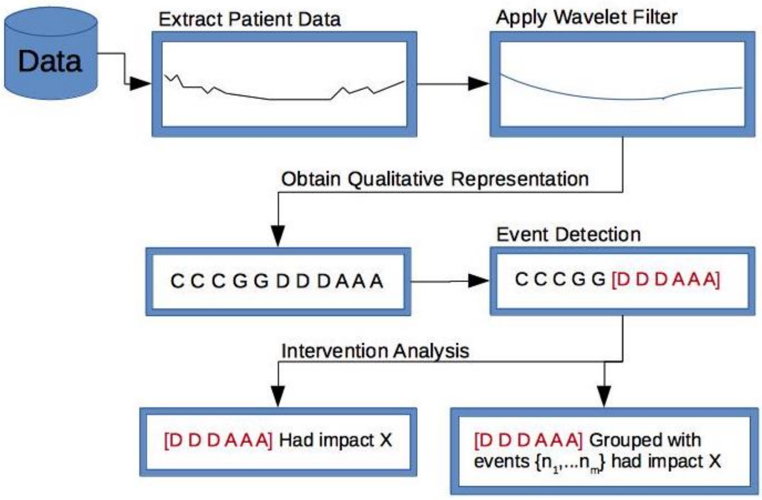


Figure 3.1: Schematics of implementation.

3.2.1 Wavelet Filter

Studies have shown data from CGM is subject to distortion. This is caused by diffusion processes and by time-varying systematic under/overestimations due to calibrations and sensor drifts [7]. Noise can trigger false positives in event detection because abrupt fluctuations overrides the true underlying derivatives of the curve [6]. Wavelet filters have been used repeatedly with CGM data and proved successful in reducing noise while retaining events such as spikes [9], [6], [10]. Figure 3.2 displays an example of wavelet filtering applied to CGM data.

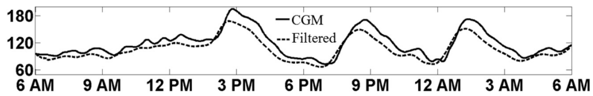


Figure 3.2: Wavelet filter applied on CGM data. Vertical axis represents glocose concentration [mg/dl]. Image courtesy of Samadi et al. [10].

3.2.2 Qualitative Representation

To identify events in the denoised CGM data feature, extraction is used. Feature extraction can be acheived by either a qualitative or quantitative method. The qualitative method offer benefits such as more transparent reasoning and ability to provide explanations for for solutions provided [11].

In qulitative representation by triangular shapes, a CGM data segment can take seven shape variables. Figure 3.3 shows the different shapes. Each is a unique combination of the first and second order derivaive on the curve of the current segment. The derivates can be read from segment adjecent points allowing a CGM data series to be presented as a sequence of shapes describing fluctuations in BG concentration.

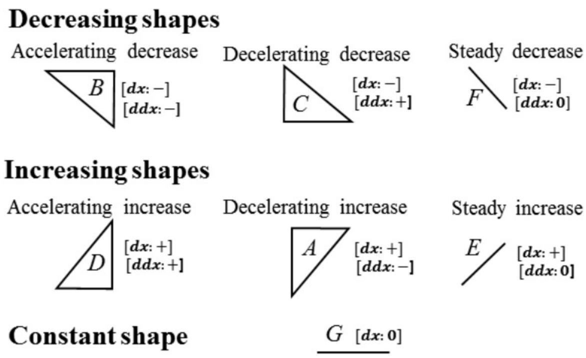
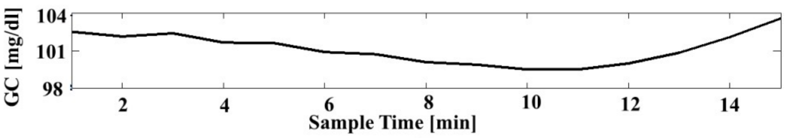


Figure 3.3: Scheme of the qualitative variables A-G. Image courtesy of Samadi et al. [10].

3.2.3 Event Detection

With the qualitative representation event detection can be performad by analysing the sequence of shapes. In figure 3.4 an event could be triggered by identifying a continously accelerating increase (for example the four sequential D's from timestep 12).



1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
G	G	G	G	B	C	B	C	B	G	G	D	D	D	D

Figure 3.4: Shape sequence representation if CGM curve. Image courtesy of Samadi et al. [10].

The detection algorithm could be [INSERT SMART ALG HERE].

3.2.4 Intervention Analysis

Intervention analysis provides a tool to asses how much a given even has changes the series (if at all) [2]. The analysis is able to detect 4 patterns:

1. Permanent constant change to the mean level.
2. Brief constant change to the mean level.
3. Gradual increase or decrase to a new mean level.
4. Initial change followed by gradual return to previous mean level.

[INSERT INSTERVENTION ANALYSIS MATH HERE]

Because changes in mean BG concentration are subtle and changes naturally takes place over a longer timespan modifications to the original approach need to be made. I suggest...

3.3 Evaluation

Training/test...

Padova...

Manual labeling...

Bibliography

[1] American Diabetes Association. "Diagnosis and Classification of Diabetes Mellitus". In: *Diabetes Care* 33.Supplement 1 (2010), S62–S69. ISSN: 0149-5992. DOI: 10.2337/dc10-S062.

[2] George EP Box et al. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

[3] N. H. Cho et al. "IDF Diabetes Atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045". In: *Diabetes Research and Clinical Practice* 138 (Apr. 2018), pp. 271–281. ISSN: 0168-8227. DOI: 10.1016/j.diabres.2018.02.023.

[4] Debbie Cooke et al. "Structured Type 1 Diabetes Education Delivered Within Routine Care". In: *Diabetes Care* 36.2 (2013), pp. 270–272. ISSN: 0149-5992. DOI: 10.2337/dc12-0080.

[5] Kathleen Dungan and Neha Verma. "Monitoring technologies–continuous glucose monitoring, mobile technology, biomarkers of glycemic control". In: *Endotext [Internet]*. MDText. com, Inc., 2018.

[6] Andrea Facchinetti. "Continuous Glucose Monitoring Sensors: Past, Present and Future Algorithmic Challenges". In: *Sensors (Basel)* 16.12 (Dec. 2016). PMC5191073[pmcid], p. 2093. ISSN: 1424-8220. DOI: 10.3390/s16122093.

[7] Andrea Facchinetti et al. "Modeling the glucose sensor error". In: *IEEE Transactions on Biomedical Engineering* 61.3 (2014), pp. 620–629.

[8] Nita Gandhi Forouhi and Nicholas J. Wareham. "Epidemiology of diabetes". In: *Medicine (Abingdon)* 42.12 (Dec. 2014). 25568613[pmid], pp. 698–702. ISSN: 1357-3039. DOI: 10.1016/j.mpmed.2014.09.007.

[9] Nicolas Magdelaine et al. “Wavelets for CGM off-line denoising”. In: (Feb. 2016). DOI: 10.13140/RG.2.1.2048.2326.

[10] Sediqeh Samadi et al. “Meal detection and carbohydrate estimation using continuous glucose sensor data”. In: *IEEE journal of biomedical and health informatics* 21.3 (2017), pp. 619–627.

[11] Venkat Venkatasubramanian et al. “A review of process fault detection and diagnosis: Part III: Process history based methods”. In: *Computers and Chemical Engineering* 27.3 (2003), pp. 327–346. ISSN: 0098-1354. DOI: https://doi.org/10.1016/S0098-1354(02)00162-X.

[12] Gisela Wilcox. “Insulin and insulin resistance”. In: *Clin Biochem Rev* 26.2 (May 2005). PMC1204764[pmcid], pp. 19–39.