

Master Thesis - Project Specification

**Meal Detection and Carbohydrate Estimation from
Continuous Glucose Monitoring data**

THONY PRICE

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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

1	Introduction	1
1.1	Project Introduction	1
1.2	Project Aim	2
1.2.1	Objective	2
1.2.2	Research Question	3
2	Background	4
2.1	Diabetes	4
2.1.1	Definition	4
2.2	Tool 1	4
2.3	Tool 2	4
2.4	Tool 3	4
2.5	Previous Work	5
3	Method	6
3.1	Data	6
3.2	Implementation	7
3.2.1	Wavelet Filter	7
3.2.2	Qualitative Representation	7
3.2.3	Event Detection	8
3.2.4	Intervention Analysis	9
3.3	Evaluation	9
	Bibliography	10

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 evaluation 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 effective insight 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 insight 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 reviewed 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 autonomous system, which fulfills the certain criteria below, can be implemented and in which configuration it performs 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 to...

2.1 Diabetes

2.1.1 Definition

Text...

2.2 Tool 1

Text...

2.3 Tool 2

Text...

2.4 Tool 3

Text...

2.5 Previous Work

Chapter 3

Method

3.1 Data

The data is collected by Steady Health during a 4,5 month pilot study including 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 collected BG data at intervals of 1-5 minutes. Patients will also log other events such as meals and exercise making those values accessible at some of the times steps.

Notation	Field	Format
P	Patient	Integer
t	Time	$YYMMDD : HHMMSS$
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. The analysis is not performed in real time but is considered a batch problem. The proposed steps of implementation can be overviewed in figure [FIGURE REF]. Each step is described in more detail in its correspondent section below.

3.2.1 Wavelet Filter

Studies have 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 as abrupt fluctuations hide 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 3.1 displays an example of wavelet filtering applied to CGM data.

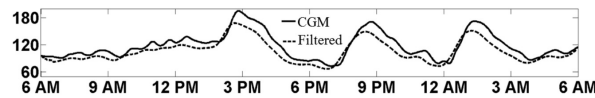


Figure 3.1: Wavelet filter applied on CGM data. Vertical axis represents glucose concentration [mg/dl]. Image courtesy of Samadi et al. [10].

3.2.2 Qualitative Representation

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

In qualitative representation by triangular shapes, a CGM data segment can take seven shape variables. Figure 3.2 shows the different shapes. Each is a unique combination of the first and second order derivative on

the curve of the current segment. The derivates can be read from segment adjacent points allowing a CGM data series to be presented as a sequence of shapes describing fluctuations in BG concentration.

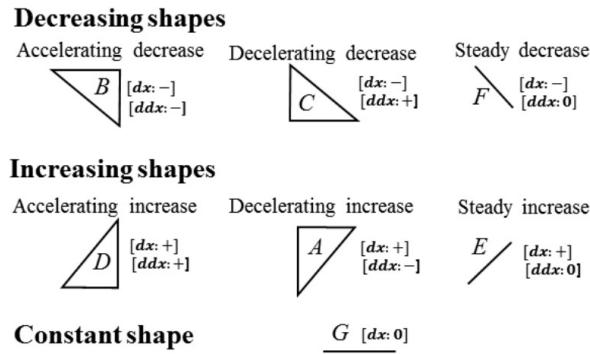


Figure 3.2: Scheme of the qualitative variables A-G. Image courtesy of Samadi et al. [10].

3.2.3 Event Detection

With the qualitative representation event detection can be performed by analysing the sequence of shapes. In figure 3.3 an event could be triggered by identifying a continuously accelerating increase (4 D's in a row from timestep 12).

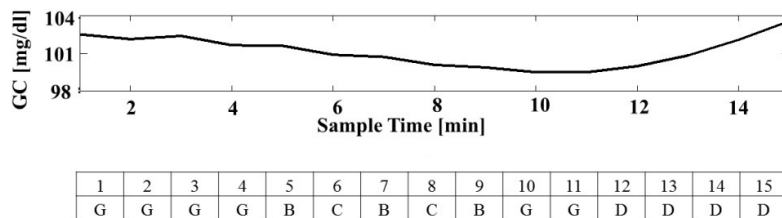


Figure 3.3: Shape sequence representation of CGM curve. Image courtesy of Samadi et al. [10].

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

3.2.4 Intervention Analysis

Intervention analysis provides a tool to assess how much a given event has changed 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 decrease to a new mean level.
4. Initial change followed by gradual return to previous mean level.

[INSERT INTERVENTION ANALYSIS MATH HERE]

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

3.3 Evaluation

Training/test...

Padova...

Manual labeling...

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