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...

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Chapter 1

Introduction

This chapter intends to provide the reader with an overview of the current state of diabetes healthcare as well as the outline and limitations 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 [5]. In 2017 the estimated prevalence of diabetes was 451 million people globally and approximately 5 million deaths were attributed to diabetes [2]. Aside from reduced life expectancy, diabetes increase the risk of multiple other conditions such as heart disease, stroke and peripheral vascular diseases [5]. 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 [2].

Diabetes is a group of metabolic diseases 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 [7]. 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 [3]. This include activities such as eating patterns, exercise and carbohydrate consumption [3].

Continuous glucose monitoring (CGM) sensors are wearable devices that measures the blood glucose frequently (usually every 1-5 minutes). The data CGM sensors provide enables analysis of a patient's historic BG fluctuations as well as predictions of its development [4].

Paragraph connecting introduction to project aim...

1.2 Project Aim

The general idea is to investigate the potential of leveraging CGM data in personalized T1D care. Currently the relevant implementations immediate actions such as alerts of high or low BG.

Extend this section...

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 analasys 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 more detailedly described in its subsequent section below.

3.2.1 Online Denoising

The data gathered with CGM may include sensor noise. Noise can trigger false positives in event detection and small fluctuations hides the true underlying derivatives of the curve. As proposed by [REF] applying a [X] filter to produce a filtered signal. [Math behind gilet goes here]. The result of aplying such filter can be seen in figure [FIGURE REF].

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 [6].

Triangular representation...

Membership degree...

3.2.3 Intervention Analysis

Detect event with impact on trend average.

3.3 Evaluation

Training/test...

Padova...

Manual labeling...

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