G Model
ARTMED-1552; No. of Pages 15
ARTICLE IN PRESS
Artificial Intelligence in Medicine xxx (2017) xxx–xxx
Contents lists available at ScienceDirect
Artificial Intelligence in Medicine
journal homepage: www.elsevier.com/locate/aiim

Temporal case-based reasoning for type 1 diabetes mellitus bolus insulin decision support☆

Daniel Brown*, Arantza Aldea, Rachel Harrison, Clare Martin, Ian Bayley

Oxford Brookes University, Oxford, United Kingdom

ARTICLE INFO

Article history:
Received 26 January 2017
Received in revised form 22 August 2017
Accepted 13 September 2017

Keywords:
Case-based reasoning
Temporal
Diabetes
Feature selection
Knowledge based systems
Similarity measures

ABSTRACT

Individuals with type 1 diabetes have to monitor their blood glucose levels, determine the quantity of insulin required to achieve optimal glycaemic control and administer it themselves subcutaneously, multiple times per day. To help with this process bolus calculators have been developed that suggest the appropriate dose. However these calculators do not automatically adapt to the specific circumstances of an individual and require fine-tuning of parameters, a process that often requires the input of an expert.

To overcome the limitations of the traditional methods this paper proposes the use of an artificial intelligence technique, case-based reasoning, to personalise the bolus calculation. A novel aspect of our approach is the use of temporal sequences to take into account preceding events when recommending the bolus insulin doses rather than looking at events in isolation.

The *in silico* results described in this paper show that given the initial conditions of the patient, the temporal retrieval algorithm identifies the most suitable case for reuse. Additionally through insulin-on-board adaptation and postprandial revision, the approach is able to learn and improve bolus predictions, reducing the blood glucose risk index by up to 27% after three revisions of a bolus solution.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Type 1 diabetes mellitus (also known as T1DM) is a medical condition in which insulin-producing cells in the pancreas are destroyed and the body can no longer produce the hormone, insulin, which in turn means that blood glucose is no longer absorbed by other cells including fat cells and muscle cells. This leads to high blood glucose levels that can have serious health consequences. A complementary hormone, glucagon, is secreted when blood glucose levels fall too low. Patients with T1DM typically have to manage blood glucose levels by introduction of insulin themselves. The size of the dose is determined through periodic monitoring of blood glucose levels and considerative of other factors such as food consumption and exercise, a complex task even for the most motivated individual [1].

Bolus insulin calculators have been shown to be effective in assisting the management of the condition [2]. However, these calculators will always produce the same result from the user's inputs unless certain settings such as the carbohydrate-to-insulin ratio (CIR) and insulin sensitivity factor (ISF) are altered, a process often guided through clinicians. Our research aims to address this issue by replacing the static formula with the ability to learn and improve bolus recommendations automatically through case-based reasoning (CBR).

The contributions of this research are a novel temporal approach to enhance case retrieval by identifying the most similar sequences of events; the incorporation of an adaptation rule for active insulin in a temporal context; and a postprandial (post-meal) revision algorithm to allow the system to learn. Additionally, a detailed comparison of single-attribute evaluation algorithms included in the Weka data mining tool [3] for the purpose of feature weighting in the similarity measure was also carried out as part of this research.

This paper is organised as follows. Section 2 explains the fundamentals of CBR, highlighting the limitation of using cases in isolation in domains like T1DM, where events in the past have consequences on the current actions. In Section 3 we describe our method for solving this problem using temporal CBR. In Section 4 we discuss and analyse Weka's different single-attribute feature

☆ This research received funding from Oxford Brookes University and the European Union Horizon 2020 research and innovation programme under grant agreement no. 689810 (PEPPER) www.pepper.eu.com.

* Corresponding author.
E-mail addresses: dbrown@brookes.ac.uk (D. Brown), aaldea@brookes.ac.uk (A. Aldea), rachel.harrison@brookes.ac.uk (R. Harrison), cemartin@brookes.ac.uk (C. Martin), ibayley@brookes.ac.uk (I. Bayley).

http://dx.doi.org/10.1016/j.artmed.2017.09.007
0933-3657/© 2017 Elsevier B.V. All rights reserved.

Please cite this article in press as: Brown D, et al. Temporal case-based reasoning for type 1 diabetes mellitus bolus insulin decision support. Artif Intell Med (2017), http://dx.doi.org/10.1016/j.artmed.2017.09.007

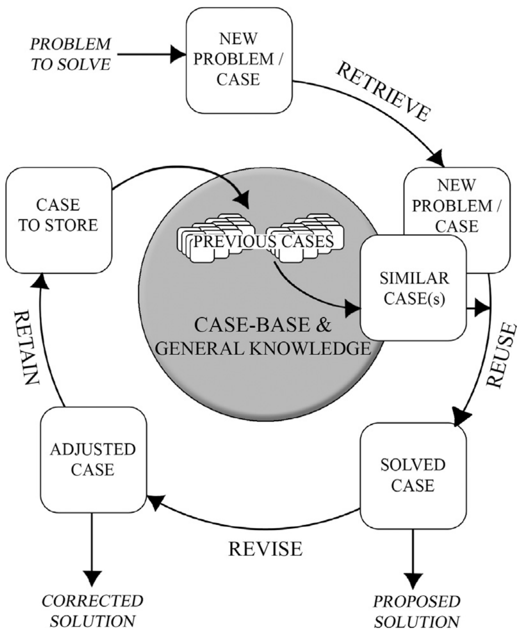

Fig. 1. R^4 CBR cycle [10].

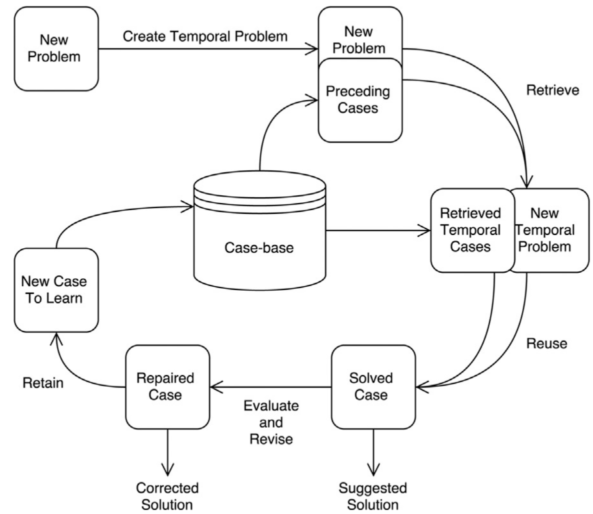

Fig. 2. Case-based reasoning model for T1DM bolus insulin advice.

selection algorithms, adopted for the purpose of feature weighting in case retrieval. This is followed by details of the data and statistical measures used for evaluating the proposed methodology in Section 5. Section 6 outlines the *in silico* results of this approach, showing the system's ability to improve results over time. Limitations and improvements in the proposed system are discussed in Section 7. Related work in the T1DM domain and temporal CBR is discussed in Section 8. Finally, conclusions reached are discussed in Section 9.

2. Case-based reasoning

Case-based reasoning attempts to mimic the human ability to recall similar situations that occurred in the past and adapt them to address new problems. The foundations of CBR can be found in the work conducted by Kolodner based on the idea of dynamic memory modelling proposed by Schank [4–6]. Several applications were developed to demonstrate the capabilities of CBR for solving real world problems, notable seminal examples include CHEF, MEDIATOR, and CASEY [7–9].

The primary knowledge store in CBR is the case-base, which is a collection of situations, scenarios, or events. Each case contains values for a set of features and a corresponding solution. In the case of T1DM, the features could be carbohydrates ingested, physical activity, time of the day, and other patient data, with the solution being the bolus insulin recommendation. The goal of CBR is to identify the case that best reflects the current situation and to adapt it to solve a new problem. One widely adopted CBR model is the R^4 model (Fig. 1) proposed by Aamodt and Plaza [10]. The R^4 model consists of four stage cycle: *retrieve*, *reuse*, *revise*, and *retain*. First, a new problem is presented to the system consisting of features and feature-values, then a similar case is retrieved. The retrieved case is then reused to solve the new problem; this may involve some form of adaptation to resolve any discrepancies between the proposed problem and the retrieved case. A solution is then presented and revised by the user or system. If the proposed solution is accepted it is then retained in the case-base as a new case. This cycle then repeats to enable the system to improve suggestions continuously as its knowledge (case-base) grows.

The majority of research and development using CBR considers each case as an isolated event. In the context of T1DM we believe that temporal effects should be factored into the retrieval step so that an individual's recent events can be taken into account. Research into temporal CBR has been relativity limited, with the majority of methods requiring specialist case representation, e.g. [11,12]. To overcome this, sequences of continuous temporal cases that are linked to each other can be merged into a singular case called an episode [13]. This method allows the temporal sequences to be compared using standard distance metrics (e.g. Euclidean distance) without the need for additional rules. Plausible episodes are generated from a new problem, which are then compared to similar retrieved episodes in order to solve the new problem. We use this formation of episodes as the foundation for our temporal approach.

3. Methodology

This section describes our proposed temporal CBR system (Fig. 2) for insulin bolus advice [14,15] based on the R^4 model.

First we identify the features that are required to represent a case and determine how the cases for T1DM bolus are modelled. This is followed by a description of how each step of the R^4 model was developed and adapted to deal with temporal information.

3.1. Case structure

Unlike other CBR systems where case features may vary from case to case, in this context the features representing a case are well-defined. The initial step taken by this research was to determine which parameters are required by bolus calculators. Through assessment of commercial and freely available smart phone bolus calculators (Accu-Chek® Aviva Expert, RapidCalc, Diabetes Personal Calculator, Diabetic Dosage, and InsulinCalc), the parameters described in Table 1 were identified. The selection method of the bolus calculator applications is described by Martin et al. [16].

The parameters shown in Table 1 allow us to describe the features of a case. It is clear that the carbohydrate intake, preprandial (pre-meal) blood glucose level, and target blood glucose level are essential case parameters as they are taking into account by all the calculators assessed.

The *Insulin Sensitivity Factor* (ISF) and *Carbohydrate-to-Insulin Ratio* (CIR) are the primary parameters used to tune the bolus calculator. However, these factors will be omitted from the cases. This is due to the fact that the ISF and CIR values are usually defined

Download English Version:

https://daneshyari.com/en/article/6853330

Download Persian Version:

https://daneshyari.com/article/6853330

Daneshyari.com