Designing a Personalised Case-Based Recommender System for Mobile Self-Management of Diabetes During Exercise

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Abstract

Increasing physical activity for type 1 diabetes patients is associated with physical and mental health benefits. However, the control of blood glucose levels for diabetes requires an effective balance of carbohydrate intake and insulin dosage to maintain a balanced blood glucose level before, during and after exercise. Existing mobile applications lack an intervention module that help users maintain an optimal blood glucose level while performing physical exercise. In this paper, we propose a personalised case-based recommender system for self-management of diabetes during exercise. One key aspect of the proposed recommender system is the recommendation of carbohydrate intake and insulin dosage to users during exercise session using visual representations. We conduct a user study with 10 type 1 diabetes patients focusing on usability of the visual representations and the helpfulness of the recommendation. Preliminary results encourage future work towards the development of a mobile application for patients.

1 Introduction

Type 1 diabetes is a chronic disease that results from insufficient insulin production by the pancreas. The loss of insulin production can cause long-term complications such as heart disease, kidney disease and stroke that are caused by hypoglycemia (blood sugar level too low) and hyperglycemia (blood sugar level too high). The quality of life for people with type 1 diabetes can be improved by gaining better control on blood sugar level (BGL) as well as increasing physical exercise. However, the need for persistent monitoring of BGL and insulin administration makes maintaining an optimal self-management regimen during physical activity a challenging task. There are many mobile apps in the Google PlayStore and the Apple AppStore that support self-management of diabetes through data logging with a goal-setting functionality. However, these mobile apps lack an intervention module that recommends a self-management plan to the users during exercise.

In this paper, we propose a personalised recommender system for mobile self-management of type 1 diabetes during exercise using a case-based reasoning approach. The mobile application aims to facilitate exercise sessions by logging user data such as intensity of the physical exercise, blood glucose levels, carbohydrate intake and insulin doses before, during and after exercise.Data collected from users for every exercise session is used as the case base to produce personalised recommendations of carbohydrate intake (CHO) and insulin dosage (INS) by retrieving previous similar sessions. Further, presenting recommendations on a small screen device can be frustrating to users. Therefore, we present the recommendations to users using visual representations.

The rest of the paper is organised as follows: in Section 2 we present previous work related to this paper. In Section 3 we describe an existing guidelines on self-management of diabetes. Our proposed personalised mobile recommender system for self-management of diabetes is described in Section 4. Further, we present the visual representations of the recommendations in Section 5. Finally, we present users' feedback on the mobile app in Section 6 and followed by our conclusions in Section 7.

2 CBR in Diabetes Management

Case-based reasoning (CBR) is an artificial intelligence approach that solves new problems using specific knowledge extracted from previously solved problems. Previous works have demonstrated the effectiveness of applying CBR to the management of chronic disease. In diabetes management, a case be identified as corresponds to a periodical visit with a physician and each case consists of the features that represent a problem, its solution and the outcome obtained after applying the solution [Marling *et al.*, 2012; Montani *et al.*, 2000]. In our work, we also identify problem, solution and outcome features, however the focus is on supporting exercise and so a case corresponds to a particular exercise session.

The types of features used in representing a case can be a numerical value (e.g. weight, blood glucose level) or a textual description (e.g. symptoms of hypoglycemia event). However, physicians often describe patients using imprecise linguistic data that cause the case base to contain imprecise knowledge and representation. To solve this problem, [El-Sappagh *et al.*, 2015] applies ontologies for case representation and a fuzzy semantic retrieval algorithm to retrieve cases. However, cases that are retrieved and recommended to users may be ignored due to lack of transparency in the recommendation. To improve users' trust and acceptability of case-based recommender systems, [Varghese *et al.*, 2015] proposed to improve the transparency of recommender systems by providing an explanatory summary that shows the reasoning process behind a proposed recommendation. In our work, we provide explanation of the reasoning for the CHO and INS recommendation using past users' similar exercise sessions.

3 Rule-based Self-Management of Diabetes Guidelines

The self-management guidelines are developed by a group of healthcare professionals and individuals with type 1 diabetes. There are three main stages in managing BGL: before, during and after an exercise session. For each exercise intensity level, the guidelines provide a specific amount of CHO or INS dosage that a user should take before exercise. Users decide on the type of exercise they are undertaking and self-adjust their BGL based on the recommended amount of CHO or INS dosage. Thereafter, users proceed to measure their BGL to decide if they are fit to start a physical exercise. If their BGL is within an appropriate range, they proceed to begin the activity. Otherwise, users need to stop exercising when their BGL is either too high or too low. In the case where the user's BGL is not too low but falls out of the appropriate range, they are discouraged from beginning any activity in a predetermined time period and taking a specific amount of CHO or INS dosage according to the guidelines, after which they recheck their BGL to make sure that it is within an appropriate range before the start of physical activity. During exercise, the users are required to check their BGL on a regular basis in order to avoid a hypoglycemia (hypo) event. They are advised to self-adjust their BGL using a specific amount of CHO or INS dosage stated in the guidelines. After completing the exercise session, users are required to check their BGL again and take a specific amount of CHO or INS dosage as recommended in the guidelines.

The rule-based guidelines are developed for all individuals with type 1 diabetes. However, they lack adaptability on CHO and INS adjustment needed for a personalised recommender system. Therefore, we propose a case-based reasoning approach to help similar users self-adjust their CHO and INS intake outside of fixed existing guideline prescriptions.

4 Case-based Recommender System for Diabetes Management

The aim of the personalised recommender system is to recommend CHO intake or INS dosage before, during and after an exercise session. Figure 1 illustrates the process of a user's exercise session. In each session, users record their BGL in three different self-management stages: *before*, *during* and *after* exercise. This helps the user monitor their BGL changes throughout the exercise session and increase their confidence in self-management during exercise.

Once the users have recorded their BGL, the system retrieves a set of similar sessions from the case base. The retrieved cases are ranked by decreasing order of similarity to the user's current session (query case) and the top 5 most similar sessions (cases) are presented to the users. In this way, users can compare and self-adjust their CHO or INS according to these similar sessions and strike a balance between high and low BGL.

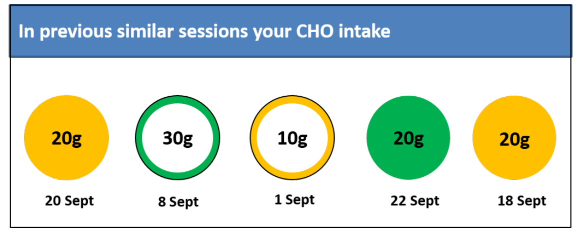

Figure 2: Visualisation

Figure 2 shows the visual representation of the recommended cases for self-adjustment using CHO based on the user's previous similar sessions. Each circle represents a previous session and the amount of CHO taken. The color of the circle represent the outcome of the user's action. A green circle represents a BGL within the balance range, a yellow circle represents a BGL slightly lower and a red circle represents a BGL either too low or too high. A filled circle indicates the amount of CHO taken is the same as the amount recommended by the rule-based self-management guidelines. Based on the scenario in Figure 2, the user may want to take 20g to 30g of CHO to achieve a balanced BGL. Finally, the user provides their feedback on the app during the exercise session.

4.1 Case Structure

A user exercise session is mapped into a case that contains all relevant data from *before*, *during* and *after* exercise. Therefore, each case consists of multiple subcases where each subcase represents a user measurement of their BGL. Formally, a case c is defined as a tuple:

$$c = \{I, U, F\} \tag{1}$$

where I contains user and session information (e.g. id, age, weight etc), U is a set of subcases and F is the feedback from the users on the session. Each subcase $subc$ is represented as follows:

$$subc = \{S, A\} \tag{2}$$

where S is the data collected from user measurement of BGL (problem description) and A is the actions taken for each measurement (solution description). A summary on the description of each feature that is relevant in each subcase is shown in Table 1.

Normally, each case will have a minimum of three subcases. However, in some situations where users are undertaking more than one hour of exercise, we record each hour of exercise as a subcase. Therefore, the size of S corresponds to the number of times users check their BGL in each session:

$$S = \{S_1 : \{f_1, f_2, f_3\}, ..., S_v : \{f_1, f_2, f_3\}\} \tag{3}$$

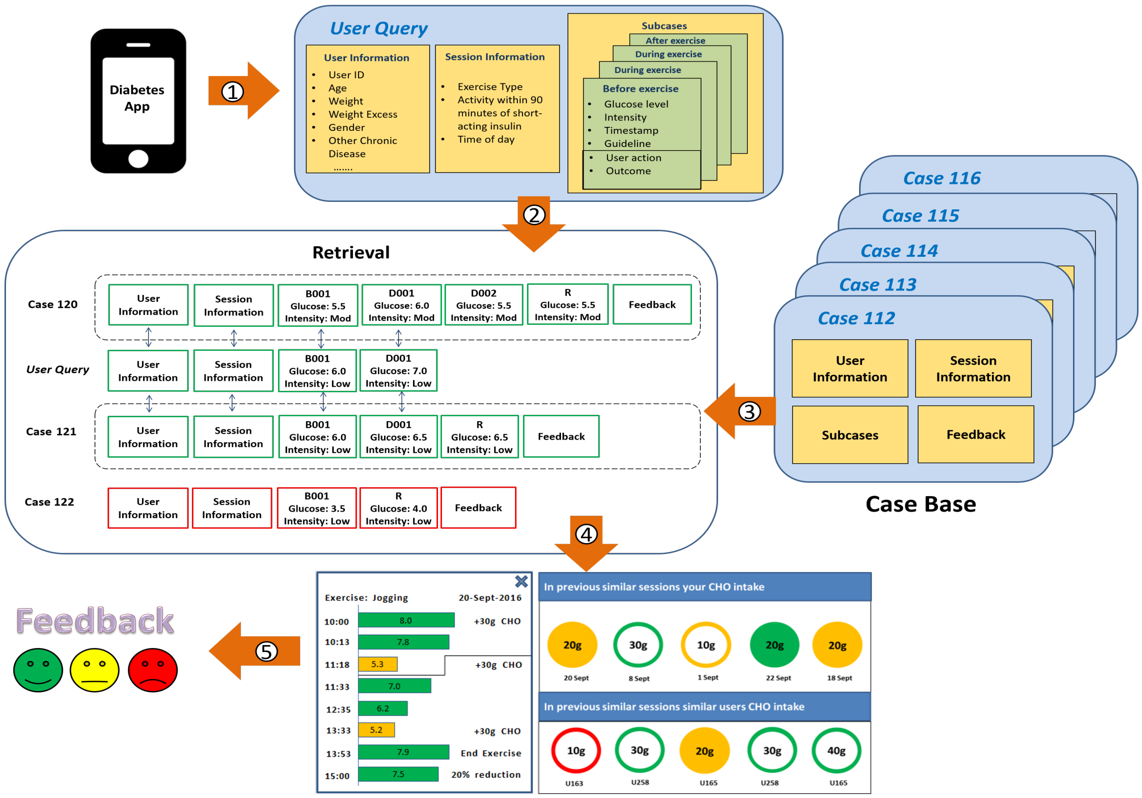

Figure 1: Overview of Personalised Recommender for Self-Management of Diabetes During Exercise

	Features	Description
f_1	intensity	Intensity level of the exercise
f_2	stageid	The three stages in self-management: before (B), during (D) and after (R) exercise
f_3	BGL	User's blood glucose level
f_4	action	The user's action to manage glucose level
f_5	outcome	The outcome of the user's action

Table 1: Subcase Features

where v is the number of times the user checks their BGL and S_i is the data collected at each measurement i. For each measurement, we consider the intensity of the exercise (f_1), self-management stage (f_2) and BGL (f_3) as the most relevant features that describe the state of the user. The corresponding action at each measurement is described in A.

$$A = \{A_1 : \{f_4, f_5\}, ..., A_v : \{f_4, f_5\}\} \tag{4}$$

Here, there are two relevant features:

- action taken by the users (e.g. amount of CHO or INS dosage) (f_4).
- BGL after user's action (f_5).

Figure 3 and 4 shows example of subcases for a user session during the exercise. Here, the user intends to perform a low intensity exercise such as *tai chi*. After one hour of exercise, the user's BGL reading is 4.0 mmol/L and requires an increase of CHO intake to boost BGL to an appropriate range. At this stage, a timer will start in the app. Once the time is up, the user will record their BGL and a subcase is created in the case base. In this example, the user takes 20g of carbohydrate and rechecks their BGL 15 minutes later before continuing to exercise. However, the outcome of the user's action (4.5 mmol/L) does not increase their BGL to a satisfactory level. Therefore, the user takes another 20g of CHO and rechecks their BGL. At this point, the user's BGL reaches a satisfactory level (5.0 mmol/L) and the user continues to exercise.

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Intensity: Low
StageId: D001
BGL: 4.0
Action: CHO 20g
Outcome: 4.5
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Figure 3: Subcase 1

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Intensity: Low
StageId: D002
BGL: 4.5
Action: CHO 20g
Outcome: 5.0
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Figure 4: Subcase 2

4.2 Case Retrieval

Case retrieval is driven by a similarity measure between the new user's exercise session and the completed sessions. In particular, we evaluate similarity of two different aspects in all self-management stages: exercise intensity and BGL. Figure 5 shows the new user's exercise session (*User Query*) and the completed sessions in the case base (Case 100 to Case 102). In this example, the user has started one hour of low intensity exercise and recorded their BGL as 5.2 mmol/L before exercise (B001). After the first hour of exercise (D001) the user's BGL is low (4.6 mmol/L) and requires to take additional CHO before continuing to exercise. At this point, the system will recommend the amount of CHO to the user based on the user's previous similar sessions.

Similarity Measures

We divide the retrieval of similar cases in two stages. In the first stage, we retrieve cases from the case base where:

- the exercise intensity is same as the user query, and
- the number of subcases per self-management stage are equal to or greater than the user query.

For instance, in Figure 5, we retrieve case 100 and 101 because they share the same exercise intensity with the user query and both cases have one subcase for each self-management stage (B001 and D001). Thereafter, we categorise the cases into two groups to recommend similar cases from the user's own previous sessions and from those of other users of the system.

We measure the similarity between the user's query case and the remaining cases using the inverse Euclidean distance as a measure of similarity across self-management stages. Essentially, we want to make sure that the retrieved cases will have a similar number of subcases to monitor the changes of BGL and the corresponding user action. Therefore, the distance between a user query q and a candidate c is calculated as follows:

$$dist(q,c) = \frac{1}{K}\sqrt{\sum_{i=1}^{K}(q_s - c_s)^2} \qquad (5)$$

Here, q_s and c_s are the BGL values in each subcase for the query and candidate case respectively and K is the minimum number of subcases across the self-management stages between a query and candidate case.

5 Visual Representation

In this work, we design five visual representations to present recommendations to users. Figure 6 shows a sample screen where users recorded their BGL in the range of 4.0 mmol/L to 5.0 mmol/L. Besides the recommendation presented by the system, there is also a timer and a message that informs the user to take 20g of CHO and recheck their BGL in 15 minutes. By default, the app will present to the user the amount of CHO intake proposed by the guideline as a reference. However, users may adjust the CHO amount if they are confident to make the adjustment. Here, the system presents a row of similar cases that shows the CHO intake of the users in previous similar sessions where the user is likely to follow the guidelines. Each circle represents a case and the date when the exercise session was undertaken. The leftmost circle is the case that is the most similar to the user query and the rightmost circle indicates the least similar case. In contrast, the second visual representation provides two sets of recommendations as shown in Figure 7. The top row shows the CHO intake of the current user in previous similar sessions. Similarly, the bottom row shows the CHO intake by other similar users of the system who had similar sessions.

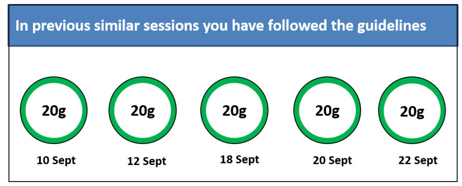

Figure 6: Circle - User's Similar Sessions

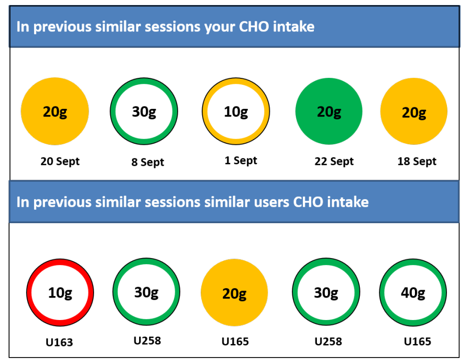

Figure 7: Circle - User and other Users' Similar Sessions

An alternative visual representation is a radar chart that shows the degree of similarity of the recommended cases to the user query (see Figure 8). The closer the case (circle) is to the centre point the higher the similarity of the case to the user query. Users are provided with options at the bottom of the screen to either view the user's previous similar sessions or other similar users' sessions.

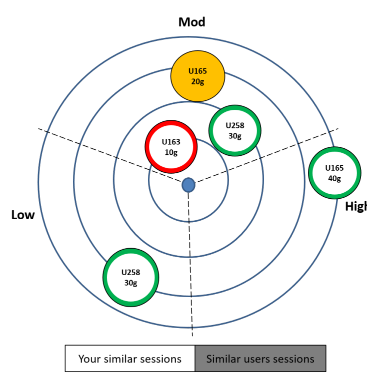

Figure 8: Alternate Visualisation - Radar Chart

Figure 6 and 7 only show the CHO intake of a particular self-management stage. In Figure 9 and 10, we consider alternative visualisations to present the details of a complete similar session to the users by using a bar chart and a line chart. These displays show the time when the participant recorded their BGL, the recorded BGL and the actions taken by the

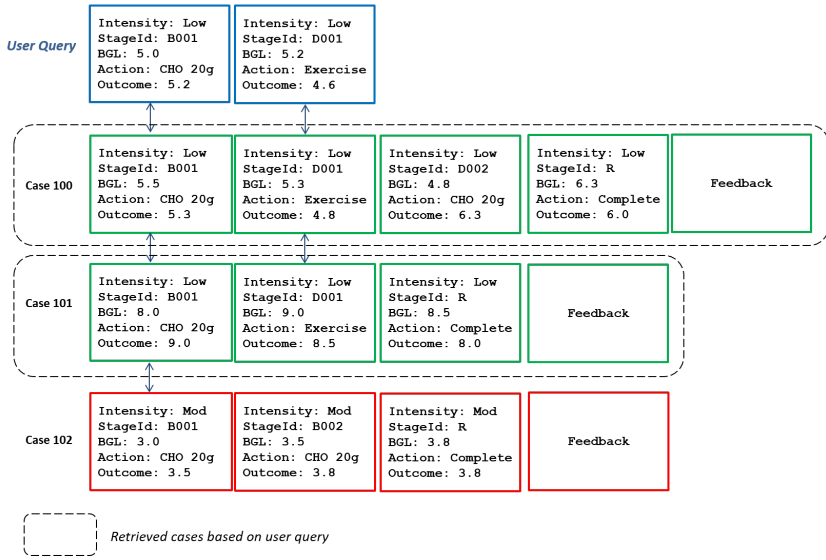

Figure 5: Case Base

user. This detailed view is accessed when the user selects a case that they want to view by clicking on the circle. Once a case is chosen, the details of the case are displayed on top of the recommended cases.

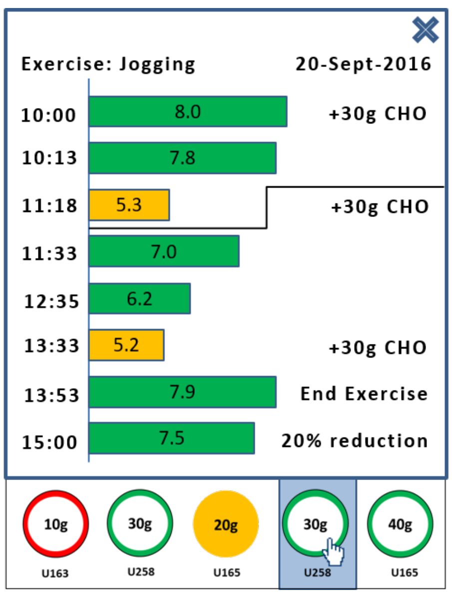

Figure 9: Detail Case View as Bar Chart

6 User Evaluation

We conducted a user evaluation on the mobile app to evaluate the usability of the five different visual representations that were used to present the recommendations as well as the recommendations provided on similar sessions. During the evaluation period, a total of 119 sessions were logged and each user had an average of 3 exercise sessions per week.

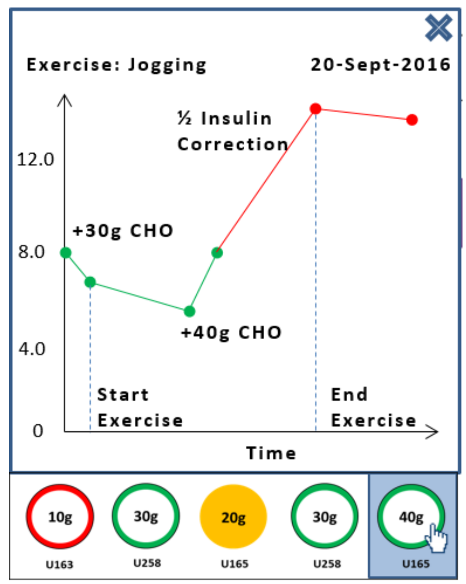

Figure 10: Detail Case View as Line Chart

The personalised recommendation of previous sessions to users received a positive feedback. In particular, the users state that looking back on the previous similar sessions to check how their BGL changed helps them self-adjust their intake of CHO and INS when doing the same intensity of exercise. However, they found the recommendation of the similar sessions from other users is mostly helpful to fill out generic information that is less individualised, such as the outcome of performing long duration physical exercise.

Feedback from participants on the visual representations suggests that the circle and line chart are the preferred options over the radar and bar chart. Specifically, the line chart provides a clearer picture on the BGL trend over the entire exercise session. One of the comments given by the users is that the bar chart would be more helpful if the user could set up a BGL threshold on the chart to show how far their BGL is from the threshold. Based on the feedback, we observed that users are not aware that the order of circles represents a degree of similarity. Therefore, future design should include a more explicit indicator to show the degree of similarity to the user's current session.

7 Conclusions

Personalised mobile recommender systems for self-management of diabetes have the potential to assist patients in maintaining an optimal blood glucose level and at the same time increase their confidence to undertake physical activity. In this paper, we propose a case-based recommender system to recommend CHO intake and insulin dosage to users during exercise. The recommendations are generated based on a user's past experience with similar exercise sessions and on other users' past experiences. We designed five visual representations to present and explain the recommendations to users. A preliminary study on the mobile app with 10 diabetes patients revealed that there are some improvements needed on the design of the visual representations. Nevertheless, feedback from users was positive and suggested that the case-based recommender system could be helpful for self-management of diabetes.

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