DeeDee - A Mobile Intelligent System able to Assist a type 1 Diabetic Through the Daily Life

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Abstract—**Type 1 diabetes mellitus is a chronic auto-immune disorder, an incurable disease affecting somebody's entire life. Yet, with proper care, a diabetic person can have a normal life and prevent complications. We believe technology could be a valuable helping tool, providing adequate decision support to diabetics. Our idea consists in realizing an intelligent system (DeeDee system) to assist a diabetic through the daily life, implemented on a mobile phone, a device to be carried on oneself along the day. The essence of this system is a new mechanism for glycaemia prediction. Existing mechanisms for glycaemia prediction are based on patient's continuous monitoring, i.e., the patient is placed into a controlled environment (a hospital), while our system aims to predict glycaemia and hence to help the patient through his/her everyday life. Compared to a continuous monitoring situation, in our case the amount of data obtained from the patient is much less. In order to correctly predict the value of glycaemia, our system relies on similar situation from diabetic's past. A key concept needed to ensure the functionality of the entire system is the construction and the management of diabetic's profiles. Each profile is automatically built such that it characterizes and groups similar situations from diabetic's life, i.e., how the diabetic's organism has reacted in these situations. In order to group correctly the similar situations, we need the context parameters recorded at that time moments. These parameters are continuously collected by the patient's mobile phone. This article proposes an integrated system capable to communicate with other medical equipments, having one main goal: to help a diabetic to have a better life.**

I. INTRODUCTION

In 2011, there were an estimated 380 million diabetic people worldwide, compared to 171 million in 2000. Of these, a total of 10% suffer from type 1 diabetes. Used to be known as juvenile diabetes, the type I diabetes is usually diagnosed in childhood, although it can occur at any age.

In diabetes, the malfunction is caused by the autoimmune destruction of the specialized cells in pancreas, the glandular organ responsible for producing insulin. As a consequence, a type 1 diabetic person has to manually administer the insulin into body, one's life depending on the ability to properly compensate the biological mechanism. Although patients are trained to independently manage the disease, for most of them this burden might become too demanding and prone to multiple errors, occurring when the amount of insulin is too high or too low and leading to sugar levels out of the acceptable limits. A low blood sugar level leads to unconsciousness, even coma, and requires emergency medical intervention, whereas high levels of blood sugar cause long-term damages to entire body.

The simple scheme of treatment, applicable to most diabetic patients, consists in the administration of insulin relative to the amount of ingested food. Using data on carbohydrate concentration in foods and through an accurate assessment of each meal, correlated with current level of BGC in the body, the amount of needed insulin can be estimated.

An accurate determination requires calculations and nutritional formulas that most diabetics cannot perform themselves. As a consequence, the diabetic patients are constantly aware of what they eat, forced to follow an extremely strict diet, i.e. every day, each meal (breakfast, lunch, dinner) containing the same concentration of carbohydrates and regularly monitoring the blood-glucose concentration (BCG) values. Moreover, in order to maintain control on BCG levels, they should have periodical episodes of physical activities throughout every day. In time, the burden a diabetic person faces grows overwhelming.

To make things even more complicated, medical studies showed evidence of other multiple factors influencing the amount of insulin needed to be administered, e.g. history of insulin administration, nature and level of physical activity, intellectual activity, daily schedule, individual general health condition, and environmental conditions. Obviously, all these lead to a very busy daily schedule, stress and depression episodes. It must be mentioned that in the past 10 years, life expectancy of patients with type 1 diabetes has not improved.

In order to help a diabetic to deal with these situations, we propose an intelligent system called DeeDee, which will be able to make prediction of patient's glycaemia levels based on patient's data collected in everyday situation, and will be capable to estimate the possible advent of hypoglycemia or hyperglycemia situations, that could be dangerous for the patient. Also, DeeDee will be able to communicate with other medical equipment and even to alert third party persons if the situation requires it (e.g., in case of hypoglycemia state).

While the implementation of the DeeDee system is in an early stage, in this paper we aim to present the ideas and concepts behind the whole system.

In Section II we analyze the existing solutions presented in literature and, based on this analysis, we propose a new solution, described in Section III. Section IV presents an overview of the entire DeeDee system. The paper ends with a section of discussion and conclusions.

II. STATE OF THE ART

Recent technologies [1] allow a continuous monitoring of the subcutaneous (s.c.) glucose concentration using specialized devices. Thus, it is possible to see the response of the patient to the treatment and also to improve the medical care in diabetes. A number of computational models have been developed with the possibility to make a short-term prediction regarding the variation of s.c. glucose concentration. Autoregressive (AR) [2] and autoregressive moving average models (ARMA) [3] are among the first models able to make an accurate prediction but only for a short-term period (30 minutes). To solve the problem of nonlinearity existed into the s.c. glucose evolution a neural network model was proposed in [4], and this model shows a better prediction but the short-term period limitation remains.

In order to make a better prediction, new additional factors have been taken into account. Information, like nutrition [5], physical activity [6] and patient lifestyle [7], were considered as having a direct impact on the variation of blood glucose concentration (BGC). Then, new series of data containing this information have been created and made publicly available. Based on a comprehensive set of data, a new feed forward model has been developed by Pappada et al. [8]. They managed to increase the prediction time horizon to 75 minutes, but the obtained error was quite big. An interesting research based on Gaussian processes has been proposed in [9], but only to modeling the blood glucose response to the patient's lifestyle. A recent and very interesting approach to predicting the s.c. glucose concentration, based on Support Vector Regression (SVR), is presented in [10] where a comprehensive set of data collected in METABO project [11] has been used. The results reported in [10] show the best prediction realized till now, for a time horizon of 120 minutes.

In order to predict the blood glucose variation and to anticipate the critical situations, we need to use a grey-box model-based control algorithm. For that, we need first-principles models that compose an internal patient model [12] [13]. Gillis et al. [14] show that, using a model-predictive control is similar to continuously solving an optimization problem. This type of control is used mainly when we want to anticipate a possible response of the system [15]. Lynch proposed a linear model predictive control (MPC) method with the aim to adjust insulin injection based on a meal ingestion [16]. To do that he adds a first-order meal disturbance model and a first-order glucose transport from plasma to interstitium to the internal model of patient. Based on the model from [17], Magni et al proposed a continuous nonlinear MPC algorithm [18]. The model was very successful for reduction of hyperglycemia states, but its computational cost is very big. Reduction of the critical states was also the objective of a feed-forward control model [19].

III. DEEDEE - CONCEPT AND ARHITECTURE

A. Information Flow in a Controlled Environment

For a diabetic placed into a controlled environment, a system able to provide information about the patient looks like in Figure 1. The advantage of a controlled environment is that medical equipments are able to collect a complete set of data that describes the patient's life for a period of time. Based on these data we can make predictions on the evolution on blood glucose concentration (BGC) for a certain time interval.

Controlled environment means that the patient parameters are continuously monitored by medical equipment (BGC level, physical activity), but also that the patient stays into a hospital, takes meals at fixed time moments, and he/she is disconnected from everyday life. Obviously, those conditions cannot be met in everyday life. Hence, if the patient is removed from the controlled environment and placed in everyday life, we assist to a massive reduction of the amount of collected diabetic data. The data that a patient records during a one day interval are very few (in average 5 BGC values and 6 CHO values) and not completely reliable.

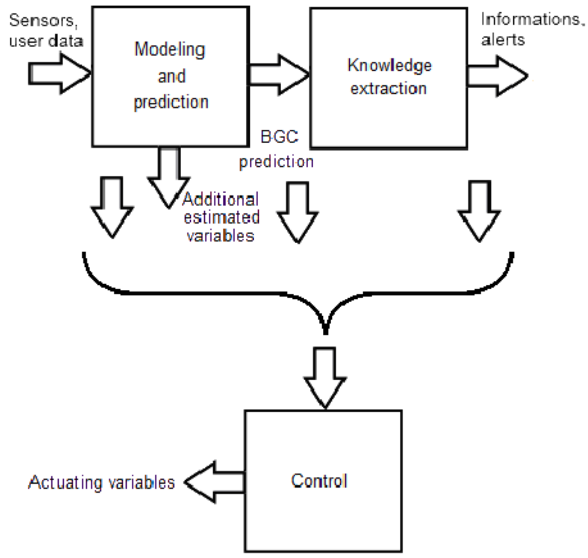

Figure 1. Information flow in a controlled environment (user = diabetic patient).

B. Behavioral model of the diabetic

For solving these problems, the DeeDee system is designed to help a diabetic to collect BGC and CHO values and also other parameters.

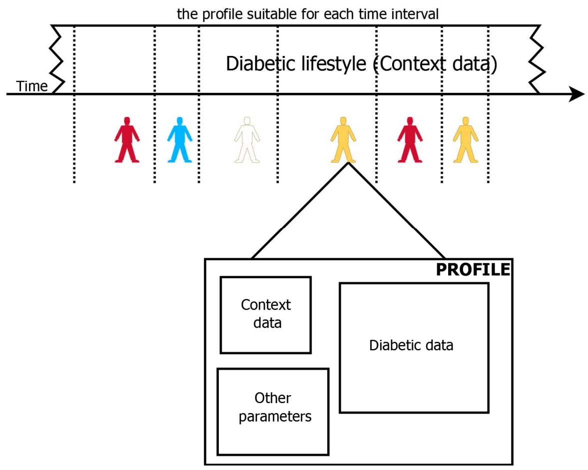

Figure 2. Patient's life as a sequence of profiles. The profile structure.

Data collection is done automatically or semi-automatically, which will increase the confidence/credibility of the data.

The key concept in realizing this objective is the construction of a behavioral model of the diabetic. The behavioral model consists of several profiles which are activated based on the patient's context that exists at a certain time moment. Each profile is realized such that it corresponds to a slice of the diabetic life and, at a certain moment, only one profile is active. For example, for a pupil we can have a school profile, an afternoon homework profile, a playing profile, a sleeping profile. As our system progresses, we can have more refined profiles. Thus, the school profile can be split to normal class hours, sports classes, test and exams, etc.

A profile (see Figure 2) is built such that it can determine the BGC variation mode for the period when the profile is active.

This will be possible after a stage of learning from similar situations determined based on context parameters. The context parameters will be chosen such that they will uniquely characterize a profile. We will call these parameters context data. Context data consists of: user's location, user's schedule, the level of physical activity, current time (hour, day of the week, month) and emotional factors.

IV. DEEDEE - SYSTEM OVERVIEW

A general view of the DeeDee system is shown in Figure 3. Next on, we will detail the components of the system.

A. *Data Preprocessing Module*

In order to have a good understanding of the lifestyle of a person we need to collect an as big as possible amount of data characterizing his/her lifestyle. For a diabetic we propose to collect the following parameters, that we will call diabetic data: BGC values, periods and levels of physical activity, meals ingested, the administrated insulin, the context of user's activity (locations, schedule, etc.) These data will be either directly collected using the mobile phone, or introduced by the user.

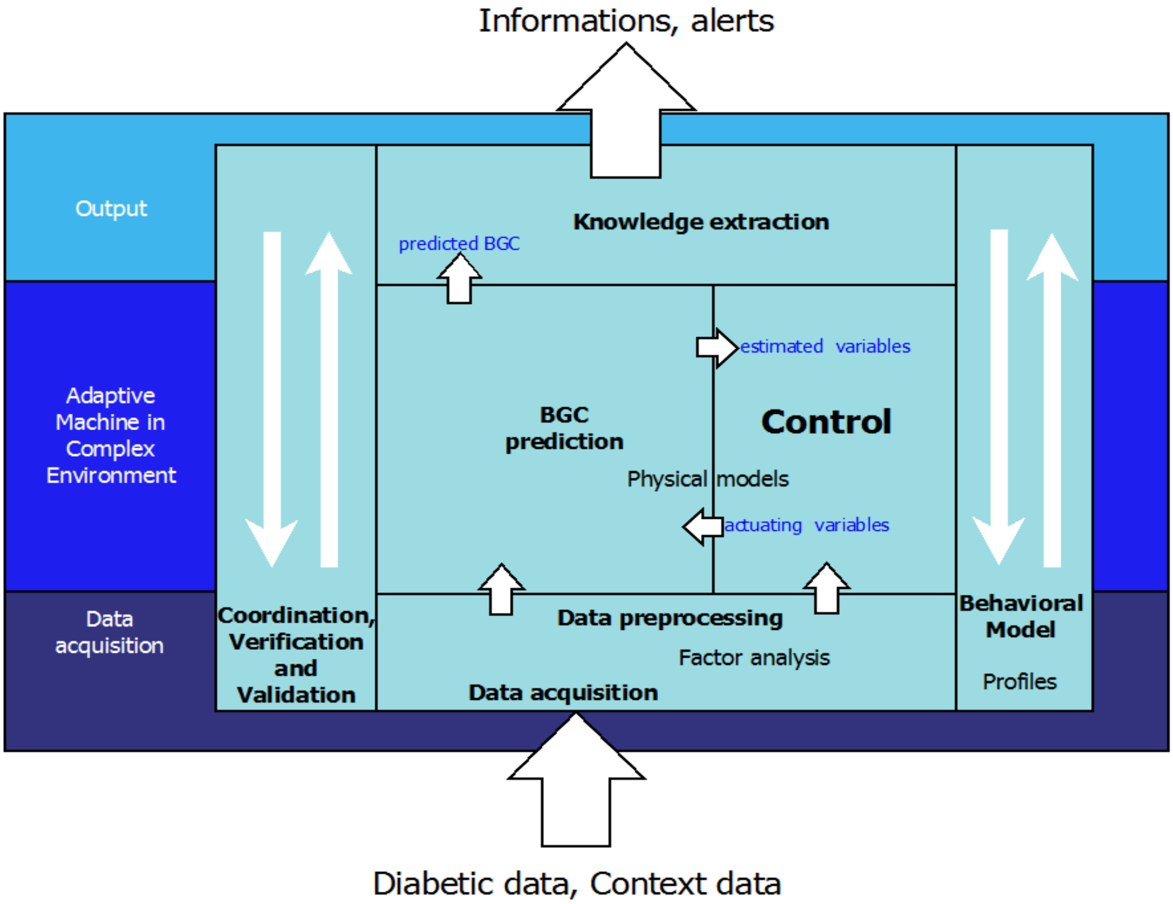

Figure 3. Informational structure of DeeDee system.

B. *BGC Prediction*

This module predicts the BGC variation using the data provided by the Data preprocessing module. This prediction takes into account the fact that BGC has two components: a basal component and a bolus component. The basal component is the amount of insulin needed by the diabetic during an entire day for general glucose demand. The bolus is the amount of supplementary insulin administrated after a meal. The two components are determined separately by different prediction models.

C. *Behavioral Model*

It contains all the profiles associated to a diabetic, and the mechanisms by which these profiles can be created, modified and deleted. Each profile is characterized in a unique way by the following context data: the time moments when the profile can be active, the level of physical activity, the geographic context, user's schedule and the emotional factors. The time moment when a user profile can become active is very important. Using this parameter we can distinguish between work day and weekend day, morning and evening, month of the year, etc.

D. *Knowledge Extraction*

The predictions offered by the BGC prediction module must be analyzed in order to extract information useful for the next period of time. The Knowledge Extraction module identifies the possible advent of hypoglycemia or hyperglycemia periods in the near future. This is done based strictly on the analysis of the BGC variation in the next time interval and of the user's profile active at that moment. The information offered to the user contains also a confidence, or credibility factor.

E. *Coordination, Verification and Validation*

It is the module that provides the coordination mechanism for the entire system. Its tasks depend on each module. At the level of the entire system, if the situation imposes, it can determine the temporary stop of the prediction system until new data will allow the system activity to resume.

F. *Control*

It is in charge with the control of BGC prediction module. It receives the estimated variables from the BGC prediction module and, based on the profiles provided by the Behavioral Model and on the first principles models, provides the actuating variables that are sent back to the prediction module.

The control should be solved in relation with the prediction. Several nonlinear models can be used with this regard including fuzzy models for nonlinear dynamic systems [20]–[32].

V. Discussion and Conclusions

DeeDee is an intelligent system designed in order to make a step further from the existing solutions, and to predict the s.c. glucose concentration based on data recorded on everyday life and not obtained from a continuous monitoring interval.

This approach is intended to improve the quality of life for a diabetic and addresses a much larger population than the solutions based on continuous monitoring. Thus, DeeDee will make multiple (one for each time horizon prediction) predictions, and based on historical data we will be able to choose the right model for the current situation. In that way we will define the "current situation" as being a new data parameter used in the prediction process.

DeeDee will be able to find situations similar to the "current situation" and based on the performance obtained in these situations, it will choose the right model, i.e., the one with the better prediction.

Because we use series of data collected from long periods of time, DeeDee will be capable to fine tune its parameters and to provide better predictions. The fine tuning will be carried out in terms of several optimization techniques adapted from different fields and associated to the definitions of appropriate optimization problems [33]–[41].

The mode of fine tuning can lead to instability in the prediction system. Hence, we will have to develop certain verification methods that will chose the best control strategy. Also, the entire system must be trustworthy in order to be used in a diabetic's every day life.

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