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The self-aware diabetic patient software agent model

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ABSTRACT

This work presents a self-aware diabetic patient software agent for representing a human diabetic patient. To develop a 24 h, stochastic and self-aware patient agent, we extend the original seminal work of Ackerman et al. [1] in creating a mathematical model of human blood glucose levels in three aspects. (1) We incorporate the stochastic and unpredictable effects of daily living. (2) The Ackerman model is extended into the period of night-time. (3) Patients' awareness of their own conditions is incorporated. Simulation results are quantitatively assessed to demonstrate the effectiveness of lifestyle management, such as adjusting the amount of food consumed, meal schedule, intensity of exercise and level of medication. In this work we show through the simulation that the average blood glucose can be reduced by as much as 51% due to careful lifestyle management. Self monitoring blood glucose is also quantitatively evaluated. The simulation results show that the average blood glucose is further dropped by 25% with the assistance of blood glucose samples. In addition, the blood glucose is perfectly controlled in the target range during the simulation period as a result of joint efforts of lifestyle management and self monitoring blood glucose. This study focuses on demonstrating how human patients' behavior, specifically lifestyle and self monitoring of blood glucose, affects blood glucose controls on a daily basis. This work does not focus on the insulin–glucose interaction of an individual human patient. Our conclusion is that this self-aware patient agent model is capable of adequately representing diabetic patients and of evaluating their dynamic behaviors. It can also be incorporated into a multi-agent system by introducing other healthcare components so that more interesting insights such as the healthcare quality, cost and performance can be observed.

1. Introduction

Diabetes is fast becoming an epidemic in today's society. The International Diabetes Federation estimates that over 371 million people suffered from diabetes and 4.8 million people died of this disease in 2012 [2]. In addition, diabetes causes a significant financial burden to individuals as well as the society, e.g., diabetes healthcare costs were estimated around 471 billion US dollars in 2012 [2]. Among the three main types of diabetes, type 2 diabetes comprises over 90% of cases [2].

Ackerman et al. proposed a linearized mathematical model to evaluate glucose-tolerance and blood glucose regulation in the 1960s [1,3]. It is originally used to predict a combination of sine and exponential wave response to an oral glucose assumption in characterizing the human glucose regulatory system. While there have been significantly more complex (glucose–insulin reactive) models developed since the advent of the Ackerman model, these models rely on more in-depth knowledge and measurement of the metabolic process, which is in general not available to the typical diabetic patient on an on-going basis. The model is defined by a set of differential equations and the solution has the form

$$x(t) = G_0 + \frac{F}{\omega} e^{\frac{-\beta t}{2}} \sin \omega t \quad (1)$$

where x is the blood glucose (BG) level as a function of time t, G_0 is fasting BG, ω is the natural frequency of the system, β is measured based on the intensity of exercise and medication and F is a measure of food intake. Their aim was to improve the distinction of normal and abnormal glucose regulation. Ackerman's work has led to significant follow-up research including the study of Jansson et al. [4] in which Ackerman's model was used to analyze the BG curves obtained during the oral glucose tolerance test in 378 cases. The intestinal glucose re-absorption levels were observed using Ackerman's model to improve the diabetes identification from normal states. Following that, Wu [5] used Ackerman's model to evaluate the degree of diabetes in a particular subject and this subject's response to medications. Wu attempted to define the effect of the medication in terms of parameter fitting of blood glucose measured from a diabetic subject with or without medication. He attempted to assess the impact of the medication based on the values of the parameters in Ackerman's model. Most recently, the Ackerman model was used by Shiang [6] in 2010, in

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their study aimed at developing methods to interpret laboratory glucose and insulin data from glucose tolerance tests, as well as to enhance the Ackerman model.

Software agent techniques have been implemented in an ever-increasing application space, from workflow management to data mining, from business process reengineering to personal digital assistants (PDAs), and from education to bioengineering. It is very difficult to precisely define an agent. Commonly accepted concepts of software agents are autonomy, social ability, reactivity, learning and negotiation [7–9]. To execute agents, they need an Agent Execution Environment (AEE), e.g., Java Agent Development Framework (JADE) provides an environment to develop agent systems compatible with FIPA protocols [10]. TRlabs Execution Environment for Mobile Agents (TEEMA) was adopted as the platform in this work because of its availability and its familiarity to us. It is developed in Java jointly by TRLabs Regina and the University of Regina. Just like any other AEE, TEEMA provides standard libraries to support various types of operations for agents such as addressing, naming, messaging, mobility, security and logging [11,12].

We incorporate the enhanced Ackerman model in the diabetic patient software agent because it provides a perspective of the condition of glucose regulation which is comparable to that which the patient will see when sampling his blood glucose levels with a blood monitoring meter. In this work, we develop a self-aware patient agent (SPA) within a mobile agent environment so that the autonomy of the agent can be used to represent the autonomy of the individual human patient. By incorporating multiple enhanced Ackerman models and a random walk (RW) model, the SPA is a 24 h circadian, self-aware, stochastic model of a diabetic patient's blood glucose levels. We identify a number of limitations which we believe apply to all published blood glucose models [13,14]: (1) The model does not extend into the night, (2) the model does not incorporate any stochastic or unpredictable behavior – which ultimately can be representative of human metabolic changes which are a response to daily life and living, and (3) the model does not address the fact that human subjects are self-aware and respond to knowledge of their own condition. Three extensions are conducted to cope with these limitations. To simulate the BG levels in a 24 h mode, we first extend the Ackerman model into nights by introducing the RW model. It is also enhanced by incorporating a random component of capturing stochastic human behaviors. The final enhancement to the model is to include the ability of the model to sample its own blood glucose, which is analogous to the human patient pricking his finger and using a drop of blood to measure his own blood glucose and then responding to the BG samples. It seems reasonable to expect that values which are out of the desired bounds would result in the human subject altering to some extent his own behavior in terms of food intake, exercise, adherence to medications, etc.

The SPA illustrates BG levels in different lifestyles that refer to diabetes treatments recommended by the Canadian Diabetes Association (CDA) which include physical activity, nutrition, medication and lifestyle management [15]. It demonstrates how the patient's lifestyle can influence the control of BG by counting the number of times BG levels fall out of the target range. Experimental results demonstrate the effectiveness of self-awareness.

2. Methods

2.1. Self-aware patient agent model architecture

Fig. 1 shows the SPA architecture. We propose multiple Ackerman models to simulate the BG in daytime, in which each Ackerman model represents each major meal (breakfast, lunch and dinner). In addition, we develop the RW model to present the BG in the night-time. By doing this, the SPA is capable of simulating the BG levels in a 24 h mode. Furthermore, the SPA incorporates a sensor *in silico* for sampling, as well as a reasoning model of behavior adjustment, which is called self-awareness. This is analogous to human patients pricking their finger and using a drop of blood to measure their own BG. The SPA also assimilates risk factors of age and health status.

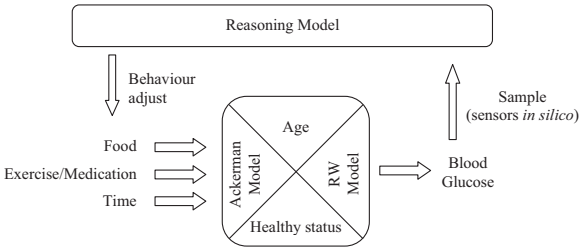

Fig. 1. Self-aware patient agent architecture.

2.2. Self-aware patient agent algorithm

The extension of the Ackerman model to incorporate the stochastic and unpredictable nature of human behavior and metabolic activity is straightforward. We first define three non-overlapping time periods in which each meal can be consumed. Within these periods a random variable is used to select the actual time of the meal. Eqs. (2)–(5) illustrate the mathematical model of the SPA. We further regulate the amount of food to be consumed to be random within a specified range, and lastly we add a component of uniform distributed random values, which are representative of the metabolic and human response to daily living.

$$\mathrm{BG}(t) = G_i + \frac{F}{\omega} e^{\frac{-\beta(t-T)}{2}} \sin\ \omega(t-T) \tag{2}$$

$$G_i = \begin{cases} \mathrm{BG}(t_0), t_0 < t \le t_1 \\ \mathrm{BG}(t_1), t_1 < t \le t_2 \\ \mathrm{BG}(t_2), t_2 < t \le t_3 \\ \mathrm{BG}(t_3), t_3 < t \le t_{0N} \end{cases} \tag{3}$$

$$T = \begin{cases} 0, t_0 < t \le t_1 \\ t_1, t_1 < t \le t_2 \\ t_2, t_2 < t \le t_3 \\ t, t_3 < t \le t_{0N} \end{cases} \tag{4}$$

$$\begin{cases} t_0 = \mathrm{Rand(breakfast\ schedule\ window)} \\ t_1 = \mathrm{Rand(lunch\ schedule\ window)} \\ t_2 = \mathrm{Rand(dinner\ schedule\ window)} \end{cases} \tag{5}$$

where $\mathrm{BG}(t)$ is the blood glucose level. t_0, t_1 and t_2 are the breakfast, lunch and dinner consumption times, respectively. t_3 is the time of 6 h after dinner has been eaten, when the SPA is assumed to be going to sleep. t_{0N} is the time breakfast is eaten the next day.

Extending the model to the nighttime is a very important issue since there are very often important changes in BG during the night. This feature has not been accounted for in any other models. While night metabolic rates vary dramatically and there are five established stages in sleep (Stages 1–4 and REM sleep) [16], we find that BG levels do not correspond closely to these sleep stages. Instead, we consider three phases of sleep-based BG interaction: light sleep (gradual decrease in BG level), deep sleep (relatively flat