Cross-Border Challenges in Informatics with a Focus on Disease Surveillance and Utilising Big-Data 77
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Combined Model for Diabetes Lifestyle Support

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Abstract. Treatment of diabetes mellitus is a public health related problem of modern healthcare. Surveys show that current methods to estimate the required amount of insulin are quite inefficient in practice as they are based on experience. This paper offers a new approach to predict the glucose level of people with diabetes. It combines two efficient models of the literature: one for nutrient absorption and one for glucose control. The combination of them tracks the blood sugar level considering nutrition composition, applied insulin and initial glucose level. Compared to already existing mixed meal models, the current version takes into account a more detailed nutrition composition (protein, lipid, monosaccharide, fiber and starch) supported by our expert dietary systems. Although the model gives satisfactory results even with parameter sets taken from literature, parameter training by genetic algorithms yields a better tracking of the patients.

Keywords. eHealth; Glucose-Insulin model; Glucose absorption; Diabetes

Introduction

Diabetes mellitus is a metabolic disease that affects our whole modern society. It is a typical disease of the modern culture mostly caused by obesity, the lack of physical activity and the changing of culinary culture. Currently, this problem hits 3% of the population [1]. Moreover, the number of the people with diabetes can reach 5% within some decades, according to current predictions [1]. This underlines the importance of diabetic lifestyle support.

In our work, we present a new approach to predict the glucose level of people with diabetes by combining a mixed meal model with a glucose-insulin one. We have focused on outpatients treated with insulin injections no matter having type 1 or type 2 diabetes [2]. For the insulin dose and timing, the patients normally use their own experience considering meals, physical activity, sports and the weather change. The main index to verify the patients' state is HbA_{1c} (Glycated hemoglobin). According to the recent surveys, these HbA_{1c} values are far from ideal in the case of most patients [3]. The gap does not seem big, but it can lead to serious complications.

The paper is structured as follows: Section 1 presents a short survey on related works. Section 2 includes the description of the proposed glucose level prediction system. Section 3 contains the result of several tests with the model, while Section 4

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discusses the obtained results. Finally, Section 5 concludes the paper and outlines future work directions.

1. Short state-of-the art

The whole metabolism can be divided into two parts: nutrient absorption and glucose control. Our method is a combination of two existing models: one for glucose absorption and another for glucose modelling system including insulin evolution.

There are models for measuring glucose absorption from meals such as the Diabetes Advisory System (DIAS) [4]. This system operates with carbohydrate as input and takes some important components (e.g., lipids, proteins) out of consideration. Many models were built after DIAS, but their base is only a simple one-compartment model. The two-compartment model of [5] represents a more precise method by using Glycaemic Indices (GI) [6] in order to make simulations closer to reality.

The evolution of insulin is the other main factor in tracking glycaemia. There are also many methods in this field [7, 8] starting with the so-called minimal model [9]. Several methods approximate this model [10]. Methods that are more sophisticated use delayed-differential equations [11] to support subcutaneous insulin depot, create better representation of the Insulin Delivery Rate, etc.

2. The proposed method

A two-compartment method [5, 12] is often used to model the effect of nutrition to blood glucose level. The model proposed by T.Arleth et al. [5] divides the digestion into two segments (Figure 1). The food proceeds through the stomach compartment followed by the intestine, where the absorption of the monosaccharide happens. In contrast to simpler methods, this model takes protein, lipid, monosaccharide, fiber and starch as input, each one having its own effect during the absorption. Moreover, the method can deal with mixed meals by using GI, and digestion overlap is handled properly as well. The whole process is based on mass balance equations.

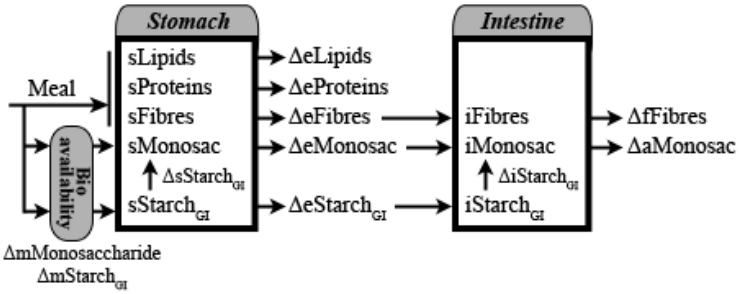

Figure 1. The process of absorption from mixed meals.

In order to model the glucose controlling process, the Delay Differential Equations (DDE) model has been chosen [12, 13]. In contrast to other methods (such as the minimal model) having a limited predictive power due to the low number of parameters, this model has several parameters supporting both type 1 and type 2 diabetics. It also

allows insulin pump or subcutaneous insulin injections as input. The method uses two subcutaneous depots (accessible and not-accessible) to simulate subcutaneous insulin absorption.

The current article focuses on analysis, for further details of the models see [14].

2.1. The algorithm

To provide a better parameter set for the model, a genetic algorithm was used (Steady State Genetic Algorithm (SSGA) with jMetal framework [15]). The initial population consisted of the parameter set of the virtual patient from [14]. The fitness of a candidate parameter set was represented by an overall error rate computed from a Single Objective genetic algorithm creation [15].

3. Results

To validate the model obtained by the combination of the models highlighted in Section 2 and introduced in [14], as a first step we had done tests on virtual patients [16]. After that, two outpatients with diabetes mellitus were examined. The first patient was a woman with Type 2 diabetes (A), while the second test involved a Type 1 diabetic man (B). Both were treated with subcutaneous insulin injections, with similar protocols and the tests were executed with the same model parameters as with virtual patients.

Patient A was treated as inpatient to adjust her inordinate blood glucose levels. During the 6 days measurement, 15 meals and 45 glucose level values were logged; the latter was measured by an ordinary blood glucose meter. In the case of outpatient B, a controlled experiment was made during 3 days with 13 meals. To log blood sugar level, a Medtronic Guardian Real-Time Continuous Glucose Monitoring (CGM) System was used, measuring the actual value every 5 minutes.

Two different kinds of tests were made with each patient. The first simulation used meal wise records, i.e. the meals were treated as separate tests. Each test was run with zero start up blood insulin level and no running glucose absorption. The second test used a whole day's data for one day long test with zero start up blood insulin level in the morning. During this test, the absorption of the insulin and the glucose from food could be in progress at the next meal as well.

The change in the three parameters after the genetic algorithm was 78% in the case of patient A and 59% in the case of patient B.

Table 1. Comparison between the Two Tests with Patient A and Patient B

Patient A – 15 meals Patient B – 13 meals		**Meal wise**		**Whole day**		**Whole day with genetic algorithm**	
		A	**B**	**A**	**B**	**A**	**B**
Average deflection (mmol/l)		4.0	2.99	3.55	2.35	3.22	2.46
Error of prediction	< 3 mmol/l	50%	65%	61%	69%	61%	73%
	< 5 mmol/l	68%	76%	79%	81%	86%	77%
	< 8 mmol/l	93%	94%	93%	100%	96%	100%

4. Discussion

The results in Table 1 show that during the whole testing period better tracking results can obtained as it takes more factors into account. The model copes with insulin absorption and digestion overlap, which results in ca. 5% improvement of the error. The average error decreased by 0.5 mmol/l.

Comparing the two patients (see Figure 2), there is more than 1 mmol/l decrease in average error if the meals are more precisely logged. There is more than 10% increase in the error rate (<3mmol/l) that represents a significant improvement to any mixed meal model and protocol reported in the literature.

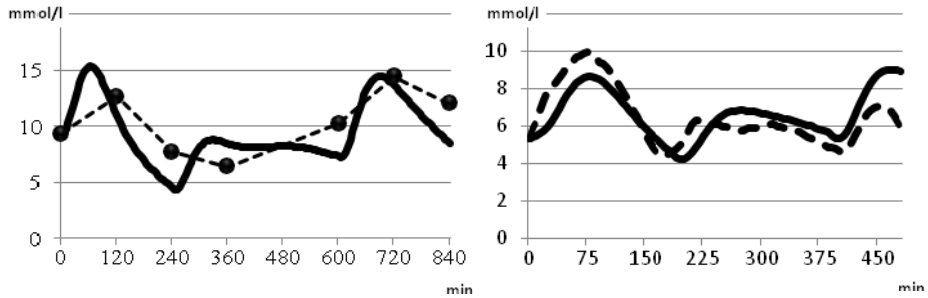

Figure 2. The fifth day of the meal wise test of patient A (left) and the first eight hours of the whole third day of patient B (right) (solid line – model estimations, dashed line – measured values)

We can also see that an ordinary blood sugar meter can lead to considerable errors in blood sugar level estimation. Analysing the meal wise test with patient A (Figure 2), it is noticeable that the patient measured a high value at 120 minutes, but the model shows even higher values between the two real-life measurements (0 min and 120 min). In this situation, the gap is small, but there could be bigger differences as well. The frequent presence of these situations can lead to higher HbA1c values.

In the case of genetic algorithm, the early tests (Table 1) show that there are more values under the margin of error (which is 3 mmol/l) for both patients with the new parameter set. This proves the need of control engineering methodologies and the efficiency of the genetic algorithm, even if it requires additional computational time.

5. Conclusion and future work

The paper presented a combined model-based approach for the short time prediction of the blood glucose level, based on the dietary log of diabetic patients. The results are satisfactory not needing any a priori identification protocol, but using genetic algorithms for model training. Further research is needed for:

- training the model to support personal variations in model parameters,
- extending the model to use also other physiological data available like physical activity and stress.

Our aim is to decrease the average error under one mmol/l, which is a significant and sufficient margin of error considering that the currently used real measurements have a similar margin of error. The results underline the importance of parameter identification. The model is currently evaluated in a clinical study with 20

rehabilitation patients as an add-on module to the specifically developed lifestyle mirror application (created at the University of Pannonia [17]). Our aim is to provide diabetics a dedicated mobile tool able to be used in their everyday life in order to predict their short time blood glucose levels.

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