A PERSONALISED APPROACH TO INSULIN REGULATION USING BRAIN-INSPIRED NEURAL SEMANTIC MEMORY IN DIABETIC GLUCOSE CONTROL

H.K. Phee¹, W.L. Tung², C. Quek³

Centre for Computational Intelligence, College of Engineering, Nanyang Technological University
School of Computer Engineering, Block N4 #2a-32 Nanyang Avenue, Singapore 639798
{¹phee0001, ²wltung, ³ashquek}@ntu.edu.sg

Abstract— Diabetes mellitus is a chronic disease with a high incidence rate worldwide. In Type-1 diabetes, the failure to produce sufficient pancreatic insulin leads to an uncontrolled increase in blood glucose. Prolong elevated blood glucose level poses significant risks of acute and chronic medical complications. Human assisted insulin injection, either through a fixed regime under the close supervision of a physician or through compartmental model schedules, is fundamentally an open-loop control system. Currently, a large amount of research has been conducted to treat Type-1 diabetes using a closed-loop insulin delivery system. The objective of this work is to investigate the use of a brain-inspired neural fuzzy system as a controller to deliver insulin in a closed-loop system for the treatment of Type-1 diabetes. In this paper, the Pseudo-Outer Product based Fuzzy Neural Network using the Yager rule of inference (i.e. POP-Yager) is employed as an intelligent controller to dispense the appropriate amount of insulin in the presence of varying meal disturbances to achieve normoglycemia for a simulated Type-1 diabetic patient.

1. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder caused by absolute or relative insulin deficiency. In 2003, according to the World Health Organization [1], at least 180 million people worldwide suffer from diabetes. Its incidence is increasing rapidly, and the number of diabetic patients is estimated to double by the year 2030. There are two subtypes of the disease: namely Type-1 [2] and Type-2 diabetes [3]. Acute and chronic medical complications due to the disease could lead to death or severe disabilities [4]. Many of these complications, however, can be significantly delayed or prevented through the tight control of the diabetic blood glucose levels within the range of 60-110 mg/dl [5]. This is achieved primarily through insulin medication coupled with strict dietary control. The objective of the insulin therapy is therefore to provide the required amount of insulin according to the varying needs of a diabetic patient. Insulin can be administered subcutaneously, intravenously or peritoneally through discrete insulin injections or continuous insulin delivery via an insulin pump [6,7].

The key to a successful management of diabetes is essentially to develop the capability to maintain long-term normoglycemia of a diabetic patient’s blood glucose level. With respect to this objective, discrete insulin injections are not ideal for the treatment of Type-1 diabetes as the regulation of the insulin hormone is an open-loop process [8]. Insulin infusion through a mechanical insulin pump, on the other hand, offers better management of the patient’s blood glucose level due to the pump’s controllable infusion rate [9]. Currently, a large amount of research has been conducted to develop a closed-loop insulin delivery system based on the insulin pump. The insulin pumps in these approaches are generally algorithmic-driven, with an avalanche of techniques proposed, investigated and reported in the literature over the years [10-14]. Classical control methods and advanced algorithms using implicit knowledge or explicit models (empirical, fundamental, or “gray-box”) of the diabetic patient have been studied and examined. These included PID [15], nonlinear PID [16], Model Predictive Control (MPC) [17,18] and Internal Model Control (IMC) [19] based techniques. All such proposed methods required some form of modeling of the glucose metabolic process of the diabetic patient and a fairly accurate knowledge of the patient’s dietary habits before a suitable control regime can be devised. However, these approaches generally result in a static insulin regulation system that performs poorly in the presence of varying meal disturbances. Hence, this paper investigates the use of a brain-inspired computational intelligence technique, specifically a neural fuzzy semantic model named POP-Yager [20], to address the effects of various dietary disturbances for the control of a diabetic patient’s blood glucose level.

In the existing literature, computational intelligence (CI) methods encompass a kaleidoscope of multidisciplinary approaches that is employed to synthesize the human intelligence in machine learning models. Among these various techniques are neural networks and fuzzy systems. Neural networks are computational models that can be trained to learn to solve complex problems from a set of numerical exemplars and subsequently generalize the acquired knowledge to solve new but similar problems. That is, they operate as universal function approximators [21,22]. However, neural networks often functioned as a black-box system as it is difficult from a human perspective to interpret the encoded knowledge and to understand the process with which the observed outputs are computed. Fuzzy systems, on the other hand, offer a computationally efficient manner to realize the approximate reasoning capability typical of humans by providing a way of processing data that allows partial set membership rather than crisp set membership or non-membership. However, fuzzy systems are often manually designed by the human experts and are generally static (non-adaptive) after construction. A study of their strengths and weaknesses subsequently shows that fuzzy systems and neural networks are complementary technologies. That is, neural networks extract information
from a set of training exemplars, while fuzzy systems employ the verbal and linguistic information provided by human experts to model the characteristics of the observed problems. The common features and characteristics of fuzzy systems and neural networks warrant their integration into one hybrid architecture to boost the hybrid system’s performance and transparency. The integrated system, popularly known as a fuzzy neural network (FNN) or neural fuzzy system (NFS) [22,23], possesses the advantages of both neural networks (e.g. learning and optimization abilities) and fuzzy systems (e.g. human comprehensible IF-THEN rules and human-like reasoning process). Thus, the connectionist structure of the hybrid system becomes more transparent and it is now possible to interpret the weight parameters following the learning stage. On the computational side, the operations of the hybrid system become interpretable to a human user as a myriad of well-established fuzzy reasoning schemes that mathematically approximates the human reasoning process can now be integrated into the system to define its internal workings. In addition, the automatic tuning of the parameters characterizing the embedded fuzzy system in a neural fuzzy system can largely draw inspirations from the learning methods proposed in the connectionist community. The above capabilities, coupled with the fact that the fuzzy rule knowledge base can now be automatically constructed from the training exemplars, enhances the use of a neural fuzzy system as an attractive proposition to model the characteristics of dynamic, complex and highly nonlinear physical systems or biological processes such as the human glucose metabolic cycle.

This paper investigates the use of a brain-inspired neural fuzzy system named POP-Yager [20] as an intelligent controller to automatically regulate the amount of insulin infused into a stimulated diabetic patient to address his varying insulin needs that arise from the different dietary intakes. Unlike the above-mentioned approaches reported in the literature, the POP-Yager based intelligent insulin regulatory system does not assume any knowledge of the dietary habits of a diabetic patient. The POP-Yager controller regulates the infusion of insulin to the diabetic patient according to the changes in his blood glucose levels. More details will be presented in a later part of the paper. The POP-Yager system is developed by mapping the Yager inference scheme [24], which possesses firm fuzzy logic foundation and adheres closely to the logical implication operations in the classical (binary) logic framework, onto the connectionist structure of the Pseudo-Outer Product Fuzzy Neural Network (POPFNN) [25,26]. The Yager fuzzy inference scheme is extended from the classical binary logical implication driven modus ponens reasoning of the statement “condition p implies consequent q” (i.e. $p \rightarrow q \Rightarrow \neg p \lor q$). The important results derived are: if p is true then q is true and if p is false, q can be true or false. This is very similar to the human way of reasoning. With respect to the application of the POP-Yager system as a controller for insulin infusion that is presented in this paper, if the glucose measurements meet the conditions of the fuzzy rules, then the administered insulin rate will be precise and accurate. If the glucose measurements do not meet the conditions of the rules, then since all possible infusion rates are possible, a mean rate that served as the base rate will be given. The brain-inspired POP-Yager system employs a two-phase training algorithm. In the first phase, the MLVQ algorithm [27] is used to cluster the data and derive the fuzzy membership functions of the inputs and outputs. In the second phase of the training, a modification of the novel one-pass rule-identification algorithm called LazyPOP [28] is used to identify the fuzzy rules. LazyPOP is a computational model of the long-term potentiation (LTP) [29,30] biological phenomenon, which has been postulated as a primary mechanism that is responsible for the learning of memory traces in the human brain [31,32].

The rest of this paper is organized as follows. Section 2 briefly describes the connectionist structure of the POP-Yager system. Section 3 presents the simulator model of a Type-1 diabetic patient and Section 4 describes the proposed POP-Yager intelligent insulin regulatory system. Section 5 analyzes the performance of the POP-Yager insulin regulatory system in controlling the blood glucose level of the stimulated diabetic patient in the presence of varying dietary meal intakes and Section 6 concludes this paper.

2. THE POP-YAGER NEURAL-FUZZY SEMANTIC MODEL

The POP-Yager [20] neural-fuzzy model is designed to be a Multi-Input Multi-Output (MIMO) fuzzy system that manifests as a seven-layer neural network. For simplicity, the computing structure of a Multi-Input Single-Output (MISO) POP-Yager that is to be employed in this paper as an intelligent controller for the regulation of the infusion of insulin is as shown in Fig 1. The computational principles in the training process of the POP-Yager system are inspired by the learning mechanisms of the biological brain. The LazyPOP algorithm is based on the Hebbian learning principle [29] that computing nodes that fired (strongly) together are wired together, just like the biological neurons in the human brain [33]. Each layer in the POP-Yager system performs a specific fuzzy operation.

The Input Layer is responsible for buffering the input data that is presented to the POP-Yager system, and the number of neurons $n$ in this layer corresponds to the number of features/inputs. Following that, the Input Label Layer fuzzifies the input data into their respective classes/clusters. These classes/clusters denote the fuzzy sets identified by the MLVQ algorithm during the training phase. For an arbitrary input $x_i$, there are $l_i$ clusters. Layer 3 is the Rule Layer. The number of neurons $n_i$ in this layer denotes the number of fuzzy rules extracted from the training data by the POP-Yager system. The weight $\alpha$ connecting an input label node to a rule node is the firing strength of the corresponding antecedent clause. The Consequent Layer contains the consequent nodes (clauses) of the POP-Yager system and each node $C_\mu$ computes the weighted sum (specified by the parameter $W_\mu$) of all rules leading to it and fired according to their importance. Layer 5 is the Output Possibility Layer,
where there are \( m \) computing nodes connected to each consequent node in Layer 4. The variable \( m \) is the number of discrete points specified during the POP-Yager training process and used to represent the membership function of an output consequent clause. Thus, \( m \) denotes the resolution of the membership function of a consequent clause. This facilitates the use of irregular-shaped membership functions instead of the commonly used trapezoidal or gaussian membership functions for more precise representation. The Output Label Layer contains the inferred fuzzy consequents (denoted by the parameters \( b_{pq} \)) of the IF-THEN fuzzy rules in POP-Yager. These inferred consequents are subsequently defuzzified into a crisp value that is presented as the output of POP-Yager at the Output Layer. Due to space constraint, the detailed descriptions of the computations performed by each layer of the POP-Yager structure shall be omitted from this paper. For the interested reader, please refer to [20] for further details on the computational process and the training algorithm of the POP-Yager system.

3. TYPE-1 DIABETIC PATIENT MODEL

The computational model used in this paper to simulate a Type-1 diabetic patient is part of GlucoSim [34], a web based educational software developed to study diabetes through the simulation of the blood glucose-insulin interactions in the human metabolic process [35]. Modeling the physiologically complex and dynamic glucose-insulin interactions requires an understanding of the physiological and chemical processes that determine the observable metabolic responses. Therefore, the study of chemical reactions and transport processes form an integrated step when modeling the glucose-insulin interactions in the human body. Several mathematical models of the insulin-dependent (Type-1) diabetes mellitus have been reported in the literature [36-39]. The GlucoSim simulator has extended and utilized two mathematical models [36] based on the pharmacokinetic diagrams of the glucose and insulin dynamics (see Fig 2 and Fig 3) which represent the transport of the plasma glucose and insulin through the major blood vessels to the capillaries in the human body [34]. Specifically, the diabetic model used in this paper is a flow-limited model for diabetes mellitus based on the work of Puckett [36]. A mass balance equation is written for each compartment in the glucose and insulin pharmacokinetic models, where the compartments denote actual body regions.
The glucose diagram (Fig 2) contains tissues including heart, brain, liver, kidney and muscle where glucose is used for energy. Glucose excretion by the kidneys and the gastrointestinal tract where exogenous glucose enters the blood are also included. On the other hand, the diagram for the insulin dynamics (Fig 3) includes the subcutaneous tissue block as a source for insulin. In the Type-1 diabetic model of GlucoSim, it is assumed that the pancreas of a diabetic patient does not produce any insulin. Hence, the insulin required to control the blood glucose level of the patient is provided exogenously via insulin injections or insulin infusion through a mechanical pump. Removal and degradation of insulin occurs mostly in the liver, kidney and peripheral tissue. The rate of degrade is one-half, one-third and one-sixth, respectively, of the insulin presented regardless of the plasma concentration of the insulin hormone. Changes in blood flow would affect these rates of insulin degradation, but the model flows are assumed to be constant [40]. Mass balances for the coupled glucose and insulin dynamic models yield a set of simultaneous ordinary differential equations that describe the glucose metabolic process of a Type-1 diabetic patient. The instantaneous blood glucose and insulin levels of the diabetic patient due to external disturbances such as insulin administrations and meal (carbohydrate) intakes can be computed by solving these differential equations using the ode23 numeric solver [41,42]. In this paper, it is assumed that the simulated Type-1 diabetic patient has a sedentary lifestyle and does not perform strenuous physical exertions such as exercises. Hence, the fluctuations in the observed plasma glucose and insulin concentrations are due to external insulin infusions and meal consumptions, as well as the physiology of the metabolic process of the diabetic patient. The generic Type-1 diabetic patient model in GlucoSim can be initialized to different physiologic profiles by specifying the body weight of the diabetic patient to be simulated.

4. PROPOSED INSULIN REGULATORY SYSTEM

4.1 POP-Yager Pump Controller

In this work, the POP-Yager system described in Section 2 is to be employed as a neural-fuzzy pump controller in a closed-loop setup (see Fig 4) to regulate the amount of insulin administered to a diabetic patient according to his varying needs based on his dietary intakes (denoted as meal disturbances). The diabetic patient is simulated using the patient model presented in the previous section. A reference signal $g_r(t)$ is introduced in the proposed insulin regulatory system to provide a relative measure ($e(t)$) between the instantaneous blood glucose level of the patient (i.e. $g(t-1)$) to a known reference value. In this paper, the reference signal $g_r(t)$ is predefined as 90mg/dl. The meal disturbance block represents the daily meal intakes of the diabetic patient that consist of varying carbohydrate contents. The regulatory system does not assume prior knowledge of the timings and carbohydrate contents of these meals. Subsequently, the metabolic state of the diabetic patient can be observed from the measurable blood insulin ($i(t-1)$) and blood glucose (i.e. $g(t-1)$) levels. In addition, various numerical derivatives of the blood glucose measurement (collectively denoted as $f(g(t-1))$ in Fig 4) such as the rate of change of $g(t-1)$ are used to characterize the nonlinear dynamics of the diabetic patient’s glucose metabolic process. The POP-Yager pump controller uses the glucose derivatives $f(g(t-1))$ and the signal $e(t)$ to compute the expected plasma insulin level $i(t)$ of the patient. This insulin level $i(t)$ is subsequently
converted to an appropriate pump infusion rate (in mU/min) to regulate the administration of the insulin hormone to the diabetic patient based on his body needs.

This highly personalized and dynamic approach to insulin administration attempts to regulate the blood glucose level of the diabetic patient to maintain long-term normoglycemia. Currently, the basic regulatory schedule of the POP-Yager pump controller is trained from paired insulin-glucose readings (and their derivatives) that are measured from a healthy person of similar physiologic profile. The objective is to model the insulin responses of this reference healthy subject. However, it is a well-established fact that significant biodiversity exists even in the glucose metabolic processes of persons with similar physiologic and dietary profiles. Hence, if the proposed POP-Yager insulin regulatory system is applied directly on a diabetic patient of unknown metabolic characteristics, it may not be therapeutically effective since the insulin schedule is derived from a reference healthy subject and not fully customized to the metabolic process of the diabetic patient. This could subsequently lead to episodes of hyper- and hypoglycemia.

4.2 Pseudo Adaptive Controller

To resolve the limitation of the proposed POP-Yager insulin regulatory system, a simple mechanism is introduced to adaptively regulate the amount of insulin being administered to an unknown diabetic patient based on his metabolic responses (see Fig 5). This improved setup includes a metabolic model of the healthy subject (henceforth denoted as the healthy person model) from whom the basic insulin schedule of the POP-Yager pump controller is derived. This healthy person model is also part of the GlucoSim software and is essentially similar to the Type-1 diabetic patient model except for the presence of a mathematical equation to simulate the normal secretion of the pancreatic insulin. The same meal profile is applied to both the healthy person and the diabetic patient (of unknown metabolic characteristics) models. Subsequently, the measured blood glucose levels for the simulated healthy person and diabetic patient are denoted as \( g_h(t-1) \) and \( g_d(t-1) \) respectively. The glucose response of the diabetic patient is evaluated with respect to that of the healthy person as shown in equation (1).

\[
E = \left[ g_k(t-1) - g_s(t-1) \right]/g_h(t-1)
\]  

(1)

Equation (5) allows the regulatory system to know how far off the diabetic blood glucose level is from the healthy person’s blood glucose level. Hence, if the glucose level of the diabetic patient is below that of the healthy person, a positive number is observed at \( E \) and that means the system should reduce the amount of insulin to be injected. On the other hand, if the patient’s glucose level is higher than the healthy reference (i.e. \( E \) is negative), more insulin should be administered to the patient to control his elevated glucose level. The value of \( E \) is limited to the range of \([-1, 1]\). To dynamically adapt the amount of insulin to be administered in order to control the patient’s glucose level so that it approaches the healthy response, an insulin modulator \( R \) is employed to modulate the computed insulin infusion rate \( \text{Inj}(t) \) of the POP-Yager insulin pump controller. The insulin modulation rate \( k \) is mathematically described by equation (2).

\[
R = k \times (1 - E) \times \text{Inj}(t) = \left(1 - \frac{E}{2}\right) \times \text{Inj}(t)
\]

(2)

The use of the modulator \( R \) enables the basic insulin schedule captured in the POP-Yager system to be dynamically adapted or customized to the needs of a diabetic patient. Alternatively, one may use \( g_h(t-1) \) and \( g_d(t-1) \) as augmented inputs to POP-Yager and do away with the modulator \( R \). However, this will reduce the flexibility of the insulin regulatory system as some form of retraining of the POP-Yager model may be required to customize the basic insulin schedule to the varying needs of different patients.

5. PERFORMANCE EVALUATION

The proposed POP-Yager pump controller is first evaluated on its modeling and prediction capabilities. As mentioned previously, the basic insulin schedule of the POP-Yager controller is derived from the paired glucose-insulin readings measured from a reference healthy subject. Hence, the POP-Yager system approximates a functional mapping between the observed glucose levels (and their derivatives) and the measured insulin responses of the healthy subject. The predicted insulin level is then used to derive the appropriate insulin infusion rate to administer the insulin to a diabetic patient of similar physiologic and dietary profiles. In this work, the training and testing data for the POP-Yager system is obtained from the healthy person model in GlucoSim. The simulated healthy person is an Asian Chinese male of age 25. His physiologic profile and typical dietary habits are listed as Table 1 and Table 2 respectively. The carbohydrate content of each daily meal is computed using a uniform distribution shown in Table 3 and normalized to his recommended daily carbohydrate intake.

<table>
<thead>
<tr>
<th>Body attributes</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>70kg</td>
</tr>
<tr>
<td>Height</td>
<td>1.73m</td>
</tr>
<tr>
<td>BMI</td>
<td>23.0</td>
</tr>
<tr>
<td>Recommended daily carbohydrate allowance (RDA)</td>
<td>350g</td>
</tr>
</tbody>
</table>

Table 1: Profile of a simulated healthy Asian Chinese male of age 25

---

2007 IEEE Congress on Evolutionary Computation (CEC 2007)
Table 2: Typical dietary habits of the simulated healthy person in GlucoSim

<table>
<thead>
<tr>
<th>Meal</th>
<th>Time (hrs)</th>
<th>Carbohydrate (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakfast</td>
<td>0830</td>
<td>38.5</td>
</tr>
<tr>
<td>Lunch</td>
<td>1230</td>
<td>108.5</td>
</tr>
<tr>
<td>Snack</td>
<td>1800</td>
<td>59.5</td>
</tr>
<tr>
<td>Dinner</td>
<td>2000</td>
<td>140.0</td>
</tr>
</tbody>
</table>

Table 3: Distribution of meal carbohydrate contents

<table>
<thead>
<tr>
<th>Meal Description</th>
<th>Distribution %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakfast</td>
<td>U(10%,20%) x Total Carb</td>
</tr>
<tr>
<td>Lunch</td>
<td>U(30%,50%) x Total Carb</td>
</tr>
<tr>
<td>Snack</td>
<td>U(10%,20%) x Total Carb</td>
</tr>
<tr>
<td>Dinner</td>
<td>U(35%,45%) x Total Carb</td>
</tr>
</tbody>
</table>

The modeling and prediction capabilities of the POP-Yager system are evaluated by analyzing its recall and generalization performances. Recall refers to in-the-sample testing where the datasets used to train and test the POP-Yager system are the same. Generalization, on the other hand, refers to out-of-sample testing where the datasets used to train and test POP-Yager are different. More importantly, the test set in the generalization evaluation process consists of novel data samples that the POP-Yager system has not previously been trained to respond to. In this assessment, the POP-Yager system is employed to predict the expected instantaneous blood insulin level observed in the simulated healthy person given his measured plasma glucose level and its derivatives. Fig 6 and Fig 7 respectively depict the recall and generalization performances of the POP-Yager system when used to predict the insulin responses of the simulated healthy person for a period of one day given his observed blood glucose measurements and derivatives. The actual observed insulin response is denoted by a dotted line while the predicted insulin level is represented by a solid line.

From Fig 6 and Fig 7, one can observe that the POP-Yager system is generally able to accurately model the complex dynamics of the blood glucose-insulin interactions in the healthy human glucose metabolic process. Although detailed analysis of the recall and generalization plots reveals that the predicted insulin response of the simulated healthy subject exhibits jerkiness and prediction of low values of the blood insulin concentration is imprecise, the POP-Yager system is able to predict the general trend of the desired healthy insulin profile. The Pearson coefficients achieved by POP-Yager for the recall and generalization evaluations are 98.5% and 89.3% respectively.

Please note that the results in Fig 6 and Fig 7 are for the recall and generalization evaluation of the POP-Yager model only. The objective is to employ POP-Yager to learn a basic schedule from the insulin response of a healthy person. This forms the basic control schedule for a diabetic patient of similar physiologic and dietary profile with respect to the reference healthy person. Therefore, although the recall and generalization performances of the standalone POP-Yager system exhibited modeling errors, this can be addressed with the adaptation of this basic insulin schedule to a customized schedule for the patient (see Fig 5).

Subsequently, the effectiveness of the proposed POP-Yager insulin regulatory system (with the insulin infusion rate modulator) is evaluated on a simulated diabetic patient with physiologic and dietary profiles that are similar to those of the reference healthy person. The diabetic patient is assumed to consume four daily meals with a total carbohydrate intake similar to that of the healthy subject. Fig 8 depicts the observed blood glucose response of the diabetic patient with respect to the measured blood glucose levels of the healthy subject for a simulation period of one day.

The peaks in the blood glucose plot of Fig 8 are due to the meals (i.e. dietary disturbances) consumed by the healthy.
subject as well as the diabetic patient. Fig 8 shows that the blood glucose level of the diabetic patient closely follows that of the reference healthy subject. This clearly demonstrates the effectiveness of the proposed POP-Yager based insulin regulatory system in dynamically responding to the varying insulin needs of the patient due to the different dietary conditions and to personalize the basic control schedule acquired by POP-Yager from the healthy reference. The system is able to maintain the diabetic patient’s plasma glucose levels very close to that of the healthy response.

6. CONCLUSIONS

This paper investigates the use of a brain-inspired neural-fuzzy system, namely POP-Yager, as a pump controller in a closed-loop insulin regulatory system for the treatment of Type-1 diabetes. The POP-Yager system is developed by mapping the Yager fuzzy inference scheme onto the generic POPFNN neural-fuzzy architecture. Unlike many existing closed-loop insulin pump systems, the objective of the proposed insulin regulatory system is to dynamically determine the insulin requirements of a diabetic patient due to the different dietary conditions that the system has no prior knowledge of. In addition, the proposed regulatory system also does not employ an explicit mathematical model of the human metabolic process to derive the insulin schedule. Instead, the blood glucose level and its derivatives as measured from a reference healthy subject are used to characterize the complex and highly nonlinear human glucose metabolic process. The POP-Yager system is subsequently employed to derive a functional mapping between the measured glucose responses and the observed plasma insulin levels. POP-Yager thus functions as a modeling system to predict the healthy insulin responses given the observed blood glucose measurements. The predicted insulin concentrations are then appropriately converted to insulin infusion rates to administer the insulin exogenously to a Type-1 diabetic patient who is unable to produce any pancreatic insulin. Since the insulin schedule used is derived from a healthy person and not customized to the metabolic process of a diabetic patient (i.e. the issue of human metabolic biodiversity), an insulin infusion rate modulator is included into the proposed regulatory system to dynamically adapt the amount of insulin administered to the patient according to his metabolic responses. This ensures that the proposed POP-Yager based insulin regulatory system can be easily adapted for use with different diabetic patients who have varying insulin needs. Simulation results have subsequently validated the feasibility of this approach. Further investigations are currently being conducted along this research direction to address Type II correction which could be construed as an “inter-patient” variability problem and the findings will be reported in future publications.

REFERENCES


