ANFIS Implementation for Autonomous Insulin Injection Systems

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ABSTRACT-The construction and learning method underlying ANFIS (adaptive-net effort-based fuzzy inference system) is presented, which is a fuzzy inference system achieve in the frame effort of adaptive net efforts. By using a hybrid learning method, the suggested ANFIS can construct the Diabetes regulation and complications trial (DCCT) has stated that, strict glycemic regulation significantly curtail the short phrase and long phrase complication of diabetes. Self tuned insulin injection system becomes necessary to inject needed amount of either insulin or glycogen based on the present condition of the Diabetic subject (patient). Developing and examination an intelligent regulation system needed to achieve the above task. An Adaptive Neuro inference system (ANFIS) is suggested to read subject to decide the displacement range of the injection pump and to generate the needed regulation signal. Comparisons with artificial neural net efforts and earlier effort on fuzzy modeling are listed and discussed. Other extensions of the suggested ANFIS and promising applications to automatic regulation and signal preparing are also suggested.

Keywords-ANFIS (Adaptive Neuro inference system), Diabetic, glucose, hypoglycemia, insulin.

I. INTRODUCTION

Diabetes is a metabolic disorder resulting from the permanent lack of insulin production from the pancreas (variety 1 diabetes) or the chronic degradation of the functionality of endogenous insulin (variety 2 diabetes), which results in raising the glucose concentration in blood because without insulin, the cellular system cannot properly convert carbohydrates such as sugars, starches, or other foods into energy usable by the body [1].

Diabetes affects almost 26 million Americans and its estimated economic cost is approximately $245 billion annually. Challenges in the management of blood sugar for Variety1 Diabetes mellitus (T1DM) patients have emerged as one of the major contributors for the increase in societal cost of the disease. Patients with T1DM may achieve better glucose regulation when they adjust their insulin doses based on their predicted blood glucose rather than reacting to their current glucose levels. Current, real times checking (wearable devices) help but inaccurate insulin doses continue to pose a problem. Converting medical message to actionable knowledge could yield better results if predictive methodologies were in place during that critical hour where poor dosing and eating decisions lead to hyper- or hypoglycemia. The objective of this effort is to develop and assess a computerized model for predicting blood glucose in patients with T1DM.

Glucose management in the human body is a regulation system and there are several variables. The predictability of future glucose levels are dephraseined by the representation of these variables using mathematical functions. These must take into account both the dynamic nature of the action profile and kinetics of insulin as well as the physical activities the patient performs, the nature and quantity of food ingested and the time of the day. In addition, there are other factors which cannot be quantified such as stress. The approaches used for measuring the quantifiable variables such as carbohydrate intake, current glucose level, basal and bolus insulin intake are far from precise.

There is a high level of variation in insulin kinetics. Traditional predictive attempts used numerical modeling, multivariate analysis, matrix algebra, and statistical methods but have had limited success [1]. Recent attempts at predictive methodologies have had better success with prediction horizons of 30 minutes [2]. This study draws upon a soft computing approach that tolerates imprecision, uncertainty and partial truth. Soft computing paradigms include computing approaches such as artificial neural net efforts, evolutionaryalgorithms, and fuzzy systems [3]. An adaptive net effort-based fuzzy inference system (ANFIS) was achieve in the frame effort of fuzzy inferences and adaptive net efforts using an artificial neural net effort [4].

The objective of the ANFIS is to integrate the best features of fuzzy systems and neural net efforts. Fuzzy systems facilitate the representation of prior knowledge as a set of constraints to reduce the optimization search space. The learning aspects of the artificial neural net efforts automate the tuning of the fuzzy regulation parameters of the model [5].In an ANFIS, the adaptive frame effort of artificial neural net efforts facilitates the learning while the qualitative aspects of human knowledge and reasoning are modeled through fuzzy identification.

The fuzzy models are found to be useful in deriving the complex relationships amongst the variables in addition to providing assistance for gathering inputs and presenting results in a meaningful way. It possesses the capability to learn from the environment using input-output pairs, self-organize its structure, and adapt parameters of the fuzzy system for predicting the output based on a set of inputs.ANFIS has been used for wide range of engineering applications including predicting individual variables, such as, software development effort estimation [6] and a chaotic time series prediction, such as water level in a reservoir over a reservoir over a period of time [7].

II. Literature survey

1.1 Glucose Regulation in Variety 1 Diabetes

The exiting effort is to regulate the blood glucose level in Variety 1 Diabetes Mellitus (T1DM) patients with a practical and flexible method that can switch amongst a finite number of distinct regulationlers, depending on the user's choice. Methods: A switched Linear Parameter Varying (LPV) regulationler with multiple switching regions, related to hypo-, hyper-, and euglycemia situations is designed. The key feature is to arrange the regulationler into a frameeffort that provides stability and performance guarantees. Results: The closed-loop performance is tested on the complete in silico adult cohort of the UVA/Padova metabolic simulator, which has been accepted by the U.S. Food and Drug Administration (FDA) in lieu of animal trials.

The outcome produces comparable or improved results with respect to previous efforts. Conclusion: The strategy is practical because it is based on a model tuned only with a priori patientinformation in order to cover the interpatient uncertainty. Results confirm that this regulation structure yields tangible improvements in minimizing risks of hyper- and hypoglycemia in scenarios with unannounced meals. Significance: This flexible method opens the possibility of taking into account, at the design stage, unannounced meals and/or patients' physical exercise.

Previous effort by the authors was presented in [28]. There, a robust H1 regulationler with a so-called Safety Mechanism (SM) and Insulin Feedback Loop (IFL) reduced the risks of hyper- and hypoglycemia in T1DM. A time-varying regulationler that reproduces this H1 regulation structure, but in an LinearParameter-Varying (LPV) frameeffort, was presented in [29]and achieved similar results. In this effort we continue topursue the LPV regulationler frameeffort. The contribution of thispaper is to consider a switched LPV regulationler that switchesbetween a selection of multiple LPV regulationlers that individuallyhave been designed for slightly different tasks (for anotherswitched-LPV approach, see [30]). Specifically, in this paperthe possibility of switching between only two LPV regulationlersis investigated, where one regulationler is dedicated to dealingwith large and persistent hyperglycemic excursions, e.g., asoccur after a meal, and the second regulationler is responsiblefor glucose regulation at all other times.

The strategyresults in a regulationler that is conservative most of the timebut switches into an "aggressive" mode when the need arises.In this effort the "need" is based purely on CGM feedback,with no need of meal announcement, via an estimator thatdetects persistent high glucose values. This is akin to theproposal of [31]. However, the notion of switched LPV regulationcan be expanded to other cases, e.g., for the regulationler tobe triggered into a "meal" mode by means of an auxiliarymeal-detection algorithm [32], [33], or by user notification. Inthis effort simulation scenarios with only unannounced mealsare investigated, as this is, in some sense, the most difficult

1.2 Long-phrase Model of the Glucose-Insulin

glucose-insulin model is introduced which fits with the clinical message from in- and outpatients for two days. Its stability property is consistent with the glycemia behavior for variety 1 diabetes. This is in contrast to traditional glucoseinsulin models. Prior models fit with clinical message for a few hours only or display some non-natural equilibria. The parameters of this new model are identifiable from standard clinical message as continuous glucose checking (CGM), insulin injection and carbohydrate estimate. Moreover, it is shown that the parameters from the model allow the computation of the standard tools used in functional insulin therapy as the basal rate of insulin and the insulin sensitivity factor. This is a major outcome as they are needed in therapeutic education of variety 1 diabetic patients.

1.3 Predictive Regulation of Blood Glucose

Automated glucose regulation (AGC) has not yet reached the point where it can be applied clinically [3]. Challenges are: accuracy of subcutaneous (s.c.) glucose sensors, physiological lag-times, and both inter- and intra-individual variability. To address above issues, we developed a novel scheme for MPC that can be applied to AGC.

An individualizable generic whole-body physiology-based pharmacokinetic and dynamics (PBPK/PD) model of the glucose, insulin, and glucagon metabolism has been used as the predictive kernel. The high level of mechanistic detail represented by the model takes full advantage of the potential of MPC and may make long-phrase prediction possible as it captures at least some relevant sources of variability [4]. Robustness against uncertainties was increased by a regulation cascade relying on proportional, integrative, derivative (PID)-based offset regulation. The performance of this AGC scheme was evaluated in silico and retrospectively using message from clinical trials. This analysis revealed that our approach handles sensor noise with a MARD of 10-14%, and model uncertainties and disturbances.

The results suggest that PBPK/PD models are well suited for MPC in a glucose regulation setting, and that their predictive power in combination with the integrated messagebase-driven (a-priori individualizable) model frameeffort will help overcome current challenges in the development of AGC systems. This effort provides a new, generic and robust mechanistic approach to AGC using a PBPK platform with extensive a-priori (messagebase) knowledge for individualization.

2.1Glucose absorption scenarios

The human blood glucose system is one of the most important systems of the human body, as energy transport is fulfilled through this complex endocrine regulation process. Because of its great importance, many models were published, most of them with phenomenological approach. The current paper focuses on a new molecular model published recently which is capable of describing the normal blood glucose household. Variety1 diabetes can be modeled by transforming the original model, and then soft computing based regulation is designed. Rough rule base is generated with subtractive clustering which is later followed by its refinement by parameter tuning. As a result, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is designed. A simple absorption model is presented in order to test the designed regulation for different absorption curves. Simulation results are in accordance with the behavior of the healthy human blood glucose system.

Variety 1 diabetes mellitus can be characterized as the loss of insulin producing beta-cells, since they are completely destroyed. Therefore, there is no human insulin production and an artificial insulin source has to be applied. It has to be regulationled by an outer loop, replacing the human glucose-insulin system. The replacement might be partially or fully automatized. Self-regulation has several strict requirements, but once it has been designed it permits not only to facilitate the patient's life suffering from the disease, but using different optimization techniques also to optimize the amount of insulin dosage to be injected.

III. SUGGESTED SYSTEM
3.1 MESSAGE COLLECTION

Patient message from consenting individuals with variety1diabetes using the Medtronic Paradigm 522 insulin pump and sensor for glucose checking were used to prepare the training and examination message sets for the ANFIS controller. The blood sugar message from the pump were used in conjunction with a diary of food consumed, carbohydrates, exercise variety and duration, and meal times for message triangulation. The patient uploaded the pump message periodically to the Care link website. The researchers then downloaded retrospective message from the Medtronic Carlike website.

The Medtronic pump message comes in comma separated value (CSV) format containing various pump event details such as sensor dislodgement and sensor glucose readings at five minute intervals. The message were further examined to depress times when the sensor was changed or the pump was not receiving message which can occur due to an event such as the participant rolling over in his or her sleep and dislodging the sensor. These messages were removed from the message set. Message sets from two patients over eight weeks were used to prototype, train, and assess the model.

3.2 MESSAGE PREPARATION

Message preparation involved identifying the message segments (frames minimum 8 bit) that had uniform input-output characteristics. The segment pertaining to the meal intake and 2 hours of subsequent period was used for analysis. The message pertaining to insulin administered in the form of basal and bolus 20 Mu/l doses were normalized to form a single input that was used to train the model. Another input, carbohydrates (in grams), was obtained from the message input by the patient and his or her diary entries. The exercise message from the patients was entered into the model using standard tables for caloric use.

3.3 ANFIS MODEL

The MATLAB version13 suite was used to build the ANFIS model and make inferences with a set of training and examination message. For training the ANFIS, six sets of message containing insulin, carbohydrate, exercise level, and time of day were used with the known output values of glucose level obtained from the glucose meter. Each of the message sets contained 24 periods for every consequent 5 minutes interval for a total duration of two hours (24 x 5 = 120 minutes). The first interval was set as the time when the patient took a meal.

The carbohydrate was assumed to start being absorbed by the body immediately when the meal is taken and be completed in 30 minutes (six 5minute intervals). The insulin dose was assumed to be absorbed uniformly in 50 minutes, and started 10 minutes after it is injected. Though the exercise message was modeled as an input, there wasn't any significant physical activity reported in the two hour period after the meal and hence it was not included in the model.

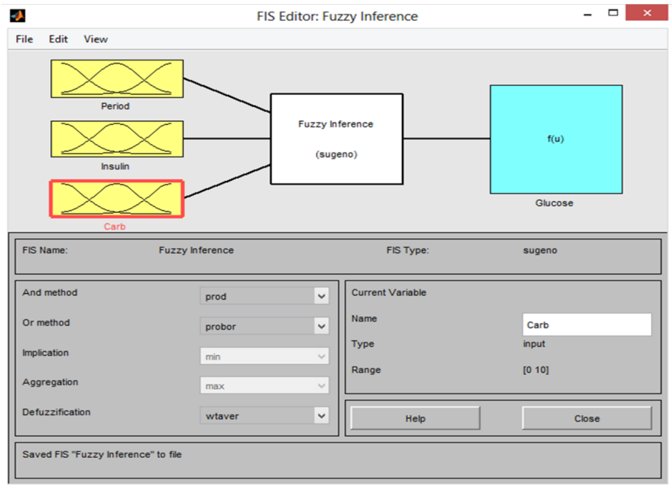

Fig 1. Fuzzy Inference model

In order to build the model that approximates the message, the training set was loaded into the MATLAB effort space. The ANFIS editor was invoked and the Grid Partition method was chosen to develop the fuzzy inference system is shown in figure 1. The number of membership functions were chosen as five. The triangular membership function was used as an input membership variety and the linear membership function was used as an output variety.

The fuzzy inference rules were then generated by MATLAB using the training message with the chosen parameters. Using the given input/output message set, the ANFIS toolbox constructed a fuzzy inference system. The inference model consisted of a number of membership functions and rules with adjustable parameters similar to that of neural net efforts. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters were chosen to tailor the membership functions to the input/output variations in the message values.

The ANFIS neuroadaptivelearning technique provided a method for the fuzzy modeling method to learn information about a message set in order to compute the membership function parameters that best allowed the associated fuzzy inference system to track the given input/output message. The fuzzy inference model generated by the ANFIS toolbox as shown in figure 2. The inference model was built using the Sugeno method since it efforts well with optimization and adaptive techniques to produce effective and efficient computations.

The membership function parameters of the fuzzy inference systems were adjusted using the combination of back propagation algorithm in combination with a least squares variety of method. This allowed the fuzzy systems to learn from the training message that was used for modeling. The ANFIS model structure generated based on the inputs and the number membership functions.

The number of inference rules generated by ANFIS is determined by the number of inputs and the number of membership functions. Since the physical activity parameter was not included in the model, there were three inputs provided to the model; meal period, glucose, and carbohydrates. The number of membership functions chosen was five and hence the ANFIS model structure generated 125 inference rules.

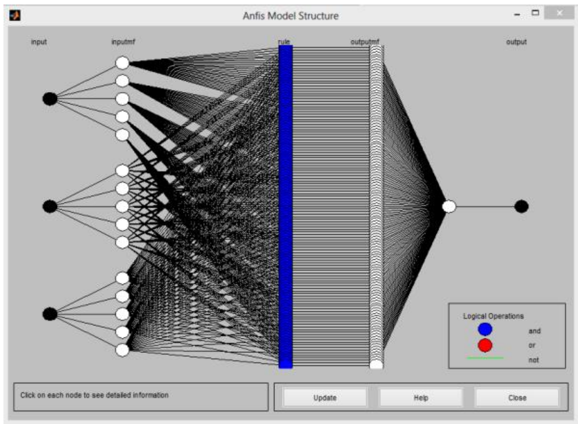

Fig 2. ANFIS Model Structure

IV.RESULT AND DISCUSSION

The goal for the predictive approach was to provide personalized aid to patients with T1DM to better manage their glucose levels. The messages were applied to the ANFIS to allow the system to create rules by which to create the predictive curve. The predictive curve very closely followed the actual message for a certain period, which was already known due to the retrospective frame effort.

Table: 1 predicted glucose level

Glucose concentration (mg/dl)	Predicted Glucose
150	4
148	5
153	20
150	18
155	40
165	46
180	50
210	59
235	68
255	76
270	86
285	90
295	100
300	108
310	115
350	120

Table: 2Actual glucose level

Glucose concentration (mg/dl)	Actual Glucose level
150	4
148	5
153	14
150	16
155	43
165	48
180	53
210	60
235	68
255	75
258	86
245	90
236	100
223	108
216	115
210	120

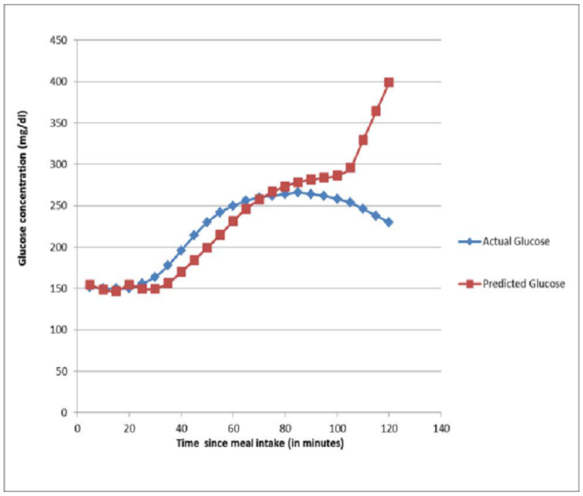

Fig:3Predicted Glucose vs. Actual Glucose

Further, we believe that the predictive period can be extended but this needs to be tested with further effort on the model with additional variables, tuning of fuzzy inference parameters, and different fuzzification/de-fuzzification approaches. The incorporation of an applied model into a device such as a smart phone within interactive PDA application coupled with insulin pump and sensor technology may further improve diabetes management.

V. CONCLUSIONS

This prescriptive approach yielded 120-minute productivity. The time period is represented in minutes on the x-axis and the glucose concentration (mg/dl) is represented on the y-axis. The ANFIS produced the predicted glucose level, which was compared to the actual glucose level and the average error of prediction was measured to assess the prediction accuracy of ANFIS. The average error of prediction= was 31 mg/dl at 30 minutes, 57 mg/dl at 1 hour, and 103 mg/dl at 2 hours. Predictability at 2 hours is less accurate than at 30 minutes because of variability in activity and insulin kinetics. It is our conclusion that this project has demonstrated the feasibility of the model. We believe that the approach will also be able to yield predictive results on a rolling basis i.e. the ANFIS can be encoded in firmware so that real time message can allow constant updating of the predictive curve.

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