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NEW GENERATION CLOSED LOOP INSULIN DELIVERY SYSTEM

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ABSTRACT

Diabetes mellitus – usually known as diabetes – is an incurable and progressive condition. It is characterized by high level of blood glucose for longer periods of time. Due to the technological advancements in glucose sensing and insulin delivery systems, Closed loop control of the disease is considered to be the optimal choice by the researchers. Recent advancements in Mobile computing systems, which are incorporated with diverse and powerful sensors, help us in providing contextual information. This information can be useful in providing the better control of the disease. This paper provides the preliminary design of Closed loop system embedded with the Contextual information, which can be helpful in improving the performance of the blood glucose control systems.

Keywords: Activity, Closed loop, Controller, Context, Diabetes, Insulin, Sensor

I.INTRODUCTION

Diabetes is a metabolic disease that affects many different parts of the body. It's a condition when a body is able to produce very little (Type 2) or no insulin. In healthy individuals, glucose is regulated within normal limits (< 154 mg/dl as recommended by American diabetes association) by insulin secretions from pancreas [1]. Maintaining glucose levels within the acceptable limits is of high importance for both diabetic as well as non-diabetic people [2]. There are two main types of diabetes namely: Type 1 (Juvenile onset) and Type 2 formerly called non-insulin dependent diabetes. Type 1 diabetes usually develops in children and adolescents (although can occur later in life). It is usually caused by an autoimmune destruction of beta cells, leading to insulin deficiency [17]. Patients require lifelong insulin injections to prevent hyperglycemia for survival. Type2 diabetes is characterized by hyperglycemia due to a defect in insulin secretion usually with a contribution from insulin resistance. Type 2 diabetes is due to lifestyle factors, including obesity, lack of physical activity, poor diet and stress [18]. Management of Type 2 diabetes is challenging and needs complex treatment, it involves integration of healthy diet, regular exercise, optimum weight control, self-monitoring of blood glucose, and medication adjustment into the daily routine over long periods [19]. Increased glucose levels in blood for a longer duration of time increase the risk of developing heart problems, brain damage, kidney failure, blindness, stroke, etc.

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This work describes the possibility of developing a closed loop control system that is capable of recognizing the user's activities for efficient management of diabetes (especially type 2 diabetes).

II. METHODOLOGY

At present patients suffering from the disease are suggested multiple daily injections as treatment or continuous delivery of insulin via an insulin pump. Another approach which has been gaining popularity in management of the disease is a closed loop control system called Artificial Pancreas (AP). AP is a system that consists of a glucose sensor for measurements, insulin delivery system (insulin pump) and a control algorithm which is used for calculating the correct dosage based on the current situation. Development of fully automated closed loop system (AP) has been of interest from many years now and various approaches have also been proposed like PID [3,4], MPC [5,6,7] , Fuzzy logic [8]. The Preliminary design we suggest is shown below Fig.1 consisting of a feedback control system (MPC) that is supplied with contextual/activity data (running, walking, stationary). This data can be easily provided by the sensors present in most of the smart phones today. Supplying this information with the current condition parameters (glucose levels, .etc) can be helpful in providing better control of the disease by regulating the glucose levels in the permitted range.

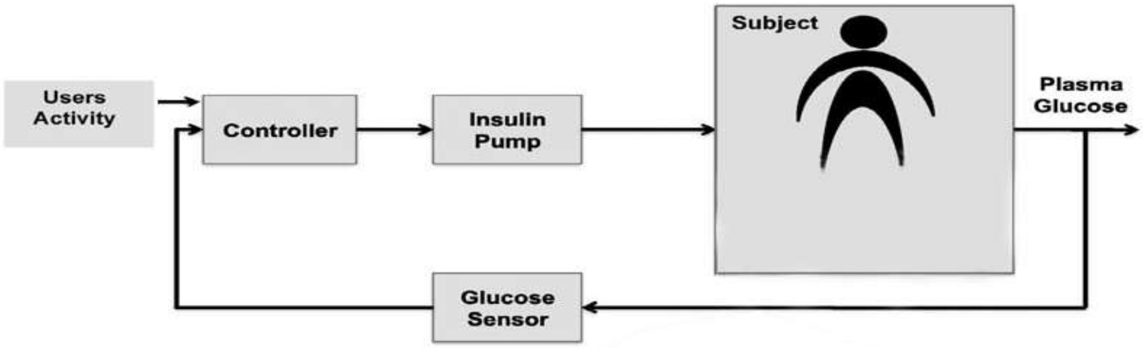

Figure. 1: Feedback Controller

III ACTIVITY RECOGNITION

Today in this age of technology smart phones are everywhere and easy to use. With their increased use and power they are incorporated with many powerful sensors like GPS, Accelerometer, Gyroscope, light sensors, audio sensors to name a few. In this section we describe various data collection methods and different activities that can be predicted after the features are extracted from the raw data.

3.1 DATA COLLECTION

Data collection can be done from smart phones because as compared to on-body devices they are easy to use and they did not disturb the users normal activity. We can create an application that will collect and control the raw data from accelerometers and store the data in files. There are different applications already that serve this purpose and are freely available on the play store.

3.2 FEATURE EXTRACTION

For the Classification of different activities we need features to be extracted from the raw sensor data. These features can be used with any Standard Classification algorithm for recognition of activities. The three axis data (x, y, z axis) is divided into segments for feature extraction. A smaller segment size may not capture the all characteristics of motion states, while larger one can introduce the noise due to involvement of multiple states [9]. Typically, a segment of one second is often utilized for activity classification, which has been validated by prior work [10]. We can have lot of features that can be applied to activity recognition [11,12], including statistical features (e.g., Mean of acceleration), time-domain features (e.g., Zero-crossings of acceleration), frequency-domain features (e.g., FFT DC component of acceleration) and discrete-domain features (e.g., Dynamic Time Warping of acceleration).

3.3 ACTIVITY PREDICTION

Once the features are extracted the prepared data can now be used with classification techniques from the data mining suite [13] to include models for predicting the users activities: decision trees, logistic regression and multilayer neural networks. TABLE 1 [15] shows the accuracies of different models in predicting the users activities.

TABLE 1: Activity Prediction

	Percentage of Records Correctly Predicted			
	Decision Trees	**Logistic Regression**	**Multilayer Perceptron**	**Straw Man**
Walking	89.9	**93.6**	91.7	37.2
Jogging	96.5	98.0	**98.3**	29.2
Upstairs	59.3	27.5	**61.5**	12.2
Downstairs	**55.5**	12.3	44.3	10.0
Sitting	**95.7**	92.2	95.0	**6.4**
Standing	**93.3**	87.0	91.9	5.0
Overall	85.1	78.1	**91.7**	37.2

IV CONTROLLER

A close-loop controller in diabetes is a system that consists of a glucose sensor for providing blood glucose measurements, an insulin pump that can be external or internal and a control algorithm. In recent years, model predictive control (MPC) has been shown to be a promising direction for an artificial pancreas control algorithm [14]. Model predictive control is an optimal control algorithm that has been used in the chemical process industries over the last 4 decades [13]. It is based on a computer control algorithm that uses an explicit process model to optimize future process response by manipulating future control moves (CM). Model predictive control optimizes every control cycle with a cost function that includes P future process instants, known as prediction horizon, and M future CM, the control horizon. In each cycle, optimization is repeated using updated process data. However, only the first CM of each optimized sequence is implemented in the process. Process input constraints are included directly such that the optimum solution prevents future constraint violation. Equation below shows the objective function:

$$J = \sum_{i=1}^{P} (r_{k+1} - \hat{y}_{k+1})^2 + \lambda \sum_{i=1}^{M} \Delta u^2{}_{k+i-1} \quad (1)$$

Where,

J is the objective function

P is the prediction horizon

M is the control horizon

k is the sample time index

λ is the weighting on the manipulated input

Δu is the manipulated input increment

r is the desired glucose set point

$\hat{y}$ is the predicted glucose output

Objective functions are used to minimize the gap between the predicted value and the desired value by manipulating the control variables. Only the first control move in the sequence is implemented, and at the next step the optimization is repeated. This approach is also known as receding horizon control.

MPC is based on past input/output records to generate a future discrete prediction. Equation (2) below describes the connection between predicted output $\hat{y}$ at instant k and past p and q output and input records, respectively.

$$\hat{y}_k = \alpha_1 y_{k-1} + \ldots + \alpha_p y_{k-p} + \beta_1 u_{k-1} + \ldots + \beta_q u_{k-q} \quad (2)$$

$\hat{y}_{k+1} = \Phi \,.\, \theta^T$

Where,

$\Phi = [\, y_{k-1} \ldots y_{k-p}\ u_{k-1} \ldots u_{k-q}\,]$ and $\theta = [\alpha_1 \ldots \alpha_p\ \beta_1 \ldots \beta_q]$

$\hat{y}_k$ predicted value

y data output records

u data inputs

θ regression vector, which can be found by a technique called LTI (linear time invariance).

In order to provide the contextual information about different activities that we extracted by methods described in the above section, the equation (2) can be modified as :

$$\hat{y}_k = \alpha_1 y_{k-1} + \ldots + \alpha_p y_{k-p} + \beta_1 u_{k-1} + \ldots + \beta_q u_{k-q} + \rho_1 z_{k-1} + \ldots + \rho_r z_{k-r}$$

(3)

$$\hat{y}_{k+1} = \Phi \cdot \theta^T$$

Where,

$\Phi = [\, y_{k-1} \ldots y_{k-p}\; u_{k-1} \ldots u_{k-q}\; z_{k-1} \ldots z_{k-r} \,]$ and

$\theta = [\alpha_1 \ldots \alpha_p\; \beta_1 \ldots \beta_q\; \rho_1 \ldots \rho_r]$

$\hat{y}_k$ predicted value

y data output records

u data inputs

θ regression vector

Providing the contextual information help the controller to take decisions based on the activity that the user is currently involved in and then manipulating the control variable based on this information is expected to further enhance the controlling capabilities of the Closed-loop controller. Fig. 2 shows the relation between the Context model and the Controller.

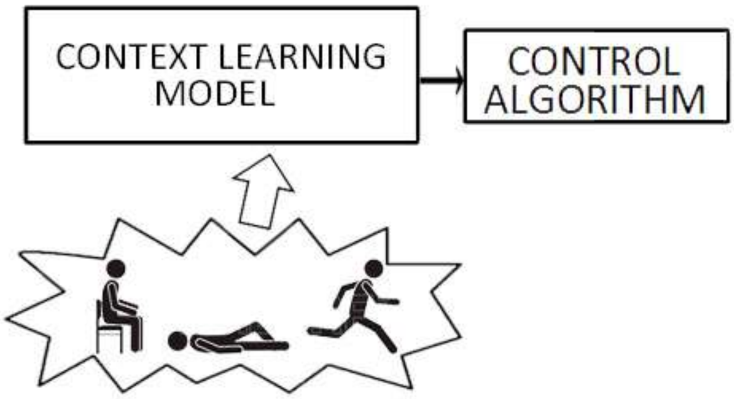

Figure. 2: Users Context

V. CONCLUSION

Diabetes management is essential for minimizing the risk of long term complications. Despite the importance of this management, it is not a simple task and a high percentage of diabetics remain uncontrolled. For its management various activities performed by the user have a significant role to play especially in type 2 diabetic people [16].

In this work we explored the possibility of designing a closed loop controller that has the ability to recognize the users activity. Further investigations will be concerned with the choice of different controllers (PID, MPC, Neural Network based) and analysis of the results.

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