A Decision Support System for Diabetic Patients: Closing the loop for MDI users*

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Abstract— **Type 1 diabetes is a chronic and a life-threatening disease, an adjusted treatment and a proper management of the disease are crucial to prevent or delay the complications of diabetes. Although, during last decade the development of the artificial pancreas has presented great advances in diabetes care, the multiple daily injections therapy still represents the most widely used treatment option for type 1 diabetes. This work presents the proposal and first development stages of a application focused on guiding patients using the continuous glucose monitors and smart pens together with insulin and carbohydrates recommendations. Our proposal aims to develop a platform to integrate a series of innovative machine learning models and tools rigorously tested together the use of the latest IoT devices to manage type 1 diabetes. The resulting systems actually closes the loop, like the artificial pancreas, but in an intermittent way.**

I. Introduction

The Internet of Things (IoT) advocates an ecosystem of interconnected objects with the ability to perform a dynamic and periodic collection of data for the purpose of analyzing and obtaining valuable information for decision making. There is a large number of areas which will be benefited from further developments of the IoT but the health sector is one of the areas with more room to take advantage of these technologies, especially in terms of the control of chronic diseases. In this sense, apart from the applications to the healthcare professional area, the empowerment of the patients themselves is considered as a key feature to design next generations of decision support tools.

An important group of these chronic diseases is well-known as diabetes mellitus, which is the result of a dysfunction of the glucoregulatory system [1]. The primary consequence of this dysregulation is a chronic hyperglycemia that is associated with long-term complications. This short note will focus in the treatment of the type-1 diabetes (T1D) which requires exogenous insulin to regulate blood glucose (BG) and is related to long-term neurological, microvascular, and macrovascular complications [2]. Over time, hyperglycemia leads to several complications such as neuropathy, nephropathy, retinopathy, and cardiovascular disease [3]. Reductions in micro- and macrovascular complications have been demonstrated in intensively treated adults with T1D [2], [4]. Hypoglycemia is a serious complication of T1D and constitutes a major concern in patient safety, being one of the most significant fears of T1D patients [5], which may lead to seizures, coma, and even death.

Over the last decade, the entire paradigm of diabetes management has been transformed due to the integration of new IoT technologies such as continuous glucose monitoring (CGM) devices and the development of the artificial pancreas (AP) along with the exploitation of data acquired by applying these novel tools. Thus, advanced data analysis techniques are also attracting an increased attention in the field because the amount of data available from patients suffering diabetes has grown exponentially. Next sections of the paper present the background, aims and design of a real-time IoT-based continuous decision support system with a novel focus on the treatment of T1D and using a novel combination of machine learning methods.

II. Background, motivation and aims

Various technologies and tools have been developed for the management of T1D. CGM systems provide glucose levels in real-time, allowing patients to perform specific actions when necessary. In addition, the combination of continuous subcutaneous insulin infusion with CGM sensor has resulted into the sensor-augmented pump systems (SAP) which have paved the way to the first automation features in commercial insulin pumps, such as low glucose suspend (LGS) and predictive low glucose management (PLGM). LGS allows basal insulin infusion to be interrupted for up to two hours if the glucose level goes below a preset threshold and the patient does not respond to the hypoglycemia alerts [6], [7], whereas PLGM suspends insulin infusion if hypoglycemia is predicted to occur within 30 minutes and resumes insulin delivery when glucose levels begin to rise [8]. In a next step towards automation, integration of closed-loop glucose control algorithms into SAP gave birth to hybrid closed-loop control systems, the so-called AP, which automatically adjusts basal insulin infusion every 5 minutes based on glucose levels [9].

Although the results achieved using the aforementioned techniques represent a great advance in diabetes care, there is still much room for improvement, especially regarding patient safety and the prevention of hypoglycemia. In addition, some of these technologies may not be suitable for all people affected by T1D, and reimbursement barriers are also an impediment to their dissemination. Therefore, MDI, which is the combination of a slow-acting analogue for basal coverage, taken once or twice a day to keep BG levels consistent and a fast-acting analogue at meal times, to control

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BG levels after eating [10], still represents the most widely used treatment option for individuals with T1D [11].

The objective of this proposal is to extend AP research to MDI therapy using a smart insulin pen and a continuous glucose monitor (CGM), that ”closes the loop” automatically guiding patient’s manual actions when needed for an improved glycemic control. Next sections of the paper present the architecture of the proposed real-time IoT-based continuous decision support system based on a novel combination of machine learning methods.

III. System Architecture and current progress of the proposal

The IoT-based architecture comprise a complete system starting from sensor nodes to a back-end server. The platform ecosystem incorporates a glucometer to collect punctual BG measurements, a CGM monitor to periodically gather BG values, a smart insulin pen to automatically register the insulin administration and a physical activity monitor for the collection of steps, heart rate and activity events. The system allows patients easily monitor their glycemic outcomes via a smart-phone application. Sensor nodes of the system are able to obtain several types of data (i.e. BG values, administered insulin, physical activity and other types of physiological data) and transmit the data wirelessly to a smart-phone unit which centralize the data acquisition.

The data gathered by the IoT ecosystem compose the source to extract the features which feed the two main subsystems: the AP tools and a the machine learning engine. The system will utilize machine learning methodologies to enhance patient safety by anticipating adverse glycemic events using: 1) mid-term (1-4 hours) continuous BG levels prediction, 2) hypoglycemia risk assessment during postprandial periods, 3) overnight hypoglycemia forecasting, and 4) clusters of different profiles according to patient condition. The AP tools consist of a series of algorithms to: a) recommend insulin boluses [12], [13], b) detect missed bolus [14], c) recommend carbohydrates intakes when high [15], and d) provide predictive alarms. These tools will be tuned according to the predictions and classifications given by the machine learning module.

Continuous predictions are driven by an implementation based on grammatical evolution (GE). The mid-term continuous predictions of BG levels are challenging because the high variability, delays of meal and insulin absorption, and lagging BG measurements. This module appropriately address such delays to provide accurate forecasts. The standalone implementation of this module is detailed and largely tested in Contreras *et al.* [16], [17]. Postprandial risk is assessed using a support vector classifier (SVC) methodology. The prediction of hypoglycemic events when a patient announces a meal allows the assessment of the impact of the insulin bolus on the postprandial response, and makes it possible to optimise the bolus to achieve safer dosages. This is detailed and validated in Oviedo *et al.* [18]. The predictions of hypoglycemic events during the night are managed by an artificial neural network (ANN) methodology. Nocturnal hypoglycemia occurrence is a critical hazard in T1D management. The module aims to allow patients to reduce the basal insulin delivery rates and/or consuming a snack in case of hypoglycemia prediction. The ANN is described in detail and tested in Bertachi *et al.* [19]. Compositional Data (CoDa) analysis and clustering techniques are applied to identify different scenarios of glycemic control. The identification of the most common situations affecting BG control allows a further customisation of therapies to the specific scenarios faced by T1D patients. Methodologies applied in this proposal are described and validated in previous studies of Biagi *et al.* [20], [21] and Contreras *et al.* [22].

The integrated data driven approach use IoT devices to increase patient safety by forecasting unwanted events using both classification and regression approaches. These techniques will be used in conjunction with a bolus calculator to calculate meal boluses and correction boluses, carbohydrate suggestions to prevent impending hypoglycemia, mechanisms to reduce postprandial hyperglycemia during missed meal boluses, preventative action to prevent nocturnal hypoglycemia, and methodologies to improved exercise management and reduce exercise-induced hypoglycemia. Basal adjustments and adaptation in insulin dosing will also be implemented.

IV. Conclusions

The IoT industry is having a drastic transformative effect on the healthcare industry. As barriers to these technologies are being slowly lowered (price, power consumption, internet access), the IoT is becoming an integral part of health monitoring and management healthcare industry. At the same time, machine learning methodologies are increasing its importance because the related increasing availability of digitized health data. Decision support tools are one of the most benefited areas which is currently being revitalized and reinforced by IoT devices and machine learning methodologies. This increment of available digital data is also occurring in the context of the diabetic populations, that along with the emerging devices and advanced methodologies, such as the AP and machine learning techniques, suggests that we are moving toward a new paradigm for management of diabetes. This new outlook proposes to achieve a personalized management and empowerment of diabetes care while customising professional practices, medical decisions, and treatments to individual patients.

The methodology proposed here has presented a novel IoT-based system aimed for the management of T1D. The system proposes the combination of CGMs and smart pens and a patient guiding process through insulin and carbohydrates recommendations. The system design integrates classic decision support tools and advanced machine learning techniques for an improved glycemic control and quality of life. The results obtained by each individual module have been previously validated and the combination of the different module are promising, especially in terms of increasing patient safety in front of glycemic events and help patients to take more accurate decisions on the management of their disease.

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