Gluco-phy, a monitor to measure glucose levels based on physiological signals

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***Abstract*—The determination of blood glucose levels can become a critical situation in patients with diabetes. Constant monitoring allows us to know if the patient is healthy. Many commercial devices use invasive methods that are uncomfortable and can cause problems such as bacterial infections and nerve damage.**

The objective of this project is to develop a monitor based on physiological sensors that can be used to measure blood glucose level easily and that any diabetic patient can use safely at home. To confirm that blood glucose levels can be measured by using biological signals such as heart rate, body temperature, galvanic skin response, non-invasive.

A non-invasive blood glucose monitoring system based on physiological signals provides a good basis for real-time monitoring of human physiological parameters in the domestic environment.

Keywords: Blood Glucose Level, Electrodermal activity, Heart Rate, Temperature, Biomedical Device.

I. Introduction

Diabetes is a chronic disease characterized by abnormally high blood glucose levels that result from impaired action of insulin and insulin slash or secretion. More than 425 million people have diabetes worldwide, and projections show that this number will increase to 629 million by 2045 [1]. While type 1 diabetes mellitus (T1DM) is characterized by autoimmune mediated destruction of insulin-producing beta cells, type 2 diabetes mellitus (T2DM) is the result of a combination of resistance to insulin and an insulin secretory defect of beta cells, which in the long term results in depletion of beta cells and eventually destruction of [1], [2].

In Ecuador, 414,414 people are affected only by T2DM, however, only 100,000 are still receiving treatment. The prevalence of T2DM in Ecuadorian patients older than 30 years is approximately 10.3 %, with an annual incidence of 115 cases per 100,000 people. In addition, diabetes is the main cause of death in Ecuador and according to the National Institute of Statistics and Censuses (INEC), in 2013, 4,695 people died from this chronic disease [3].

People with diabetes are at increased risk of nephropathy, retinopathy, auto neuropathy, peripheral neuropathies that can lead to lower limb amputation, disease cardiovascular and cerebrovascular accident [2].

To pre-detect diabetes or monitor blood glucose levels, it is necessary to obtain blood samples, which is an invasive method that should be changed as soon as possible. These techniques turn out to be more efficient, although they are the ones that carry the most risks since there could be negligence on the part of medical personnel or carelessness of the patient may occur, which can lead to a bacterial infection. [2], [4].

Therefore, to avoid such discomfort, a non-invasive method of testing blood glucose is preferred. One of the methods proposed in this project is to obtain the skin potential response (SPR) with a sensor to measure the electrodermal activity. Electrodermal Activity studies the variation of electrical characteristics of skin. EDA is a good indicator for human stress because it is related to the sympathetic nervous system. [5], [16]. SPR (named also endosomatic EDA) measures the nervous pulses which activate sweat glands [16].

It has recently been shown that with diabetes, the reduction of moisture in the stratum cornea increases the galvanic resistance of the skin. This is because diabetes is associated with alterations in skin homeostasis of the dermis. This results in dry skin, vascular neuropathy, and impaired wound healing [6]. SPR can be measured with a simple setup, without injecting current into the body, and it is less sensitive to the electrodes impedance and skin impedance slow variations [17].

In addition, this project aims to detect changes in blood volume in the microvascular bed of the tissue using photoplethysmography (PPG). With this optical technique, the light absorption and scattering properties of the skin capillaries can be observed, as the blood vessels of the finger (sensor site) expand and contract with every beat. The reflected signal is reproduced as a pulse wave near the detector. Various parameters such as blood pressure (BP), respiratory rate, systolic volume, pulse transit time (PTT), heart rate variability can be analyzed. IAC (HRV), arterial stiffness and blood glucose levels using the PPG technique [7], [8].

Using a PPG sensor to measure ECG is a good idea to create a BGL measurement system that is accurate. Such is

the fact that many articles have been found that suggest that hypoglycemia can generate abnormalities in the ECG signal [10], [11]. For example, it has been seen that an elongation of the QT interval and an increase in heart rate can be generate [11]. On the other hand, it has also been seen that the use of ECG for the estimation of glucose levels can be an innovative and cheap option to invasive traditional glucose measurement systems that require a finger prick [9], [12] . An example of an ECG-based system is the one proposed in the article by Gusev, Guseva and Poposka [12].

The last sensor is the temperature sensor. According to a Picard, the ambient temperature can influence heart rate and sympathetic response [13]. Since our sensors are based on these parameters it is important to include a temperature sensor in the system.

II. General Objective

- Create a monitoring device capable of measuring glucose levels in the blood through the physiological signals of heart rate, Skin Potential Level and temperature, easy to use at home.

III. Materials and Methods

The system consists of hardware and software. Before explaining each part of the system, its operation is summarized in figure 1.

A. Skin Potential Measurement

SP refers to the variation of the electrical conductance of the skin in response to sweat secretion [14]. This data is collected by applying a low, undetectable, and constant voltage to the skin and then measuring how the skin potential Level Changes. This can be done with devices that measure the electrical signal recorded by electrodes applied to the skin [15].

The circuit used for the SP measurement consist of an IC LM324, resistors (100Kω , 1Kω, 3.3Mω), capacitors (1μF), two Velcro skin electrodes. The IC LM324 serves as an Differential Operational Amplification, which mean it will amplify the difference between both electrodes on the patients skin with a gain of 100dB, since skin potential is measured in mV [19]. Then, a low pass filter of 5 Hz frequency, which is suitable for this kind of signals. The circuit is shown in Fig 2.

B. Photoplethysmography Measurement

To monitor the Heart Rate, a Pulse Sensor connects to the Arduino UNO micro-controller. The module includes a microchip's MCP6001 Op-Amp, resistors and capacitors that form an R/C filter network. It also has a reverse protection diode to prevent damage if the power leads are accidentally reversed. The circuit was connect to the microcontroller as the figure 3 shows.

C. Temperature Measurement

For the body temperature, an LM35 transistor was used with a 100 Ohms Resistor and 1μF Capacitor connected to ground to filter noise, as shown in Figure 4.

D. BGL Model prediction

To test and find the correlation between the physiological signals and the blood glucose levels, literature was revised. A similar circuit and correlation is found by Saad et al. [18]. For this prototype, the same correlation formula is used.

$$y = -2.33x + 10.83$$

Where y is the BGL and x is the skin potential measured.

E. Signal Processing

All sensors connected to the microcontroller Arduino UNO.Then, the signals received were averaged in order to smooth the signals. with the following code.

```
int numReadsppg = 10;
int senseppgSum = 0;
for(int i = 0; i < numReadsppg; i++){
  senseppgSum +=analogRead(PulseSensorPurplePin);
  delay(1);
}
int senseppgAve =senseppgSum/numReadsppg;
int Signal= senseppgAve;
int numReadsvout = 10;
int senseSum = 0;
for(int k = 0; k < numReadsvout; k++){
  senseSum +=analogRead(sensorPin);
  delay(1);
}
int senseAve =senseSum/numReadsvout;
vout= senseAve*0.004;
int numReadstemp = 10;
int sensetempSum = 0;
for(int j = 0; j < numReadsvout; j++){
  senseSum +=analogRead(PulseSensorPurplePin);
  delay(1);
}
int sensetempAve =sensetempSum/numReadstemp;
rtemp= senseppgAve*0.0488;
ngl= vout*(-2.33)+ 10.83;
Serial.print(Signal);
Serial.print(",,");
//delay(1000);
Serial.print(vout);
Serial.print(",,");
//delay(1000);
Serial.print(rtemp);
Serial.print(",,");
//delay(1000);
Serial.print(ngl);
Serial.println(",,");
delay(1000);
}
```

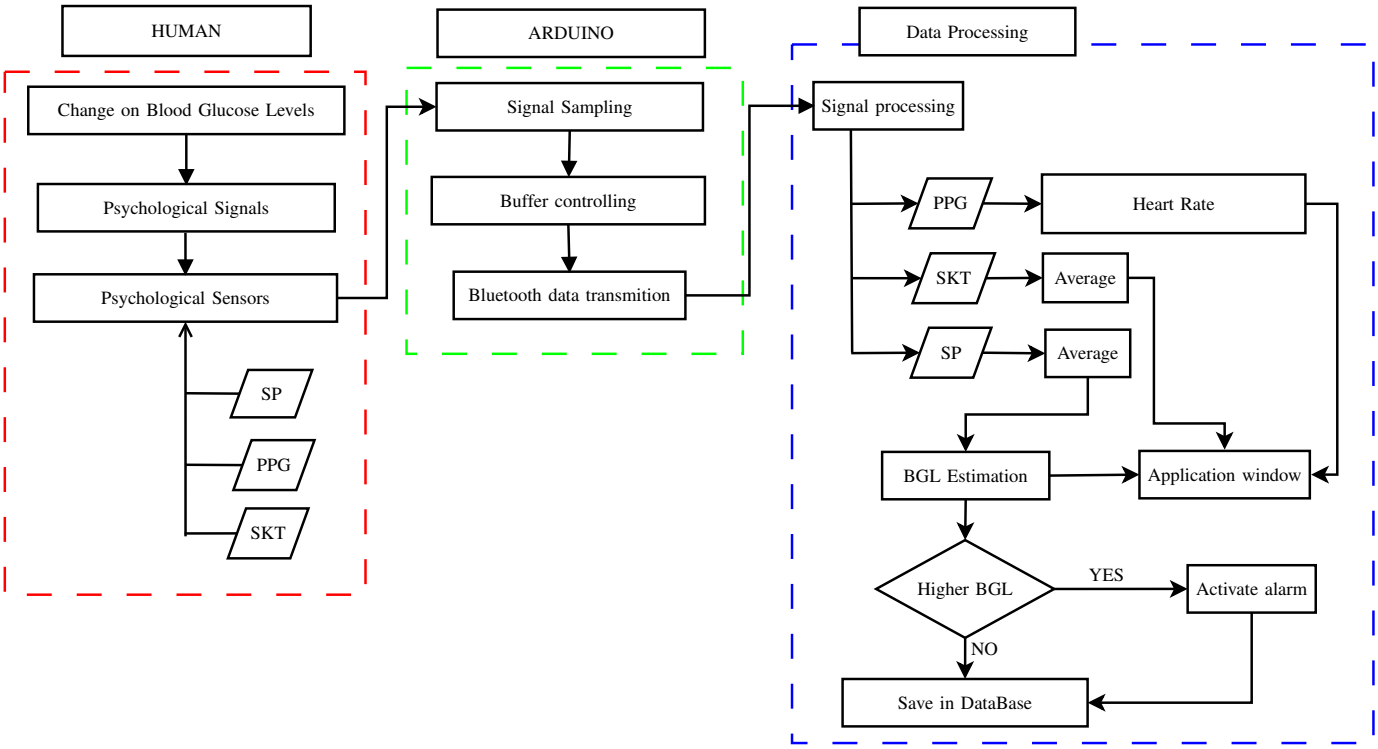

Fig. 1: System configuration and operation

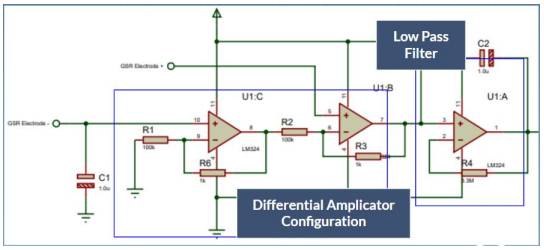

Fig. 2: SPR Circuit with DC Differential Amplifier and Low Pass Filter

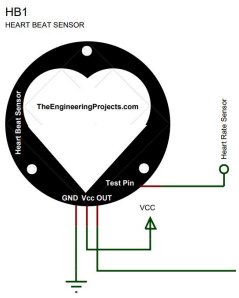

Fig. 3: Arduino Heart Beat module connections

This signal is then send via Bluetooth using an HC-05 Module that allows an easy communication between the arduino UNO microcontroller and a cellphone or computer.

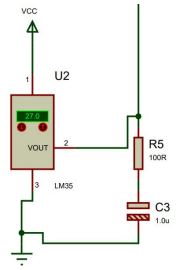

Fig. 4: LM35 transistor circuit connections

Fig. 5: Principal screen programming blocks

F. Application Development

The Application is developed using MIT App Inventor, Google Sheets and Google Forms. It consist of three screens. A principal screen in which the user can select to add a measurement to the database, consult the database or leave the app, the block are shown in figure 5 .

The second screen consists of the connection between the

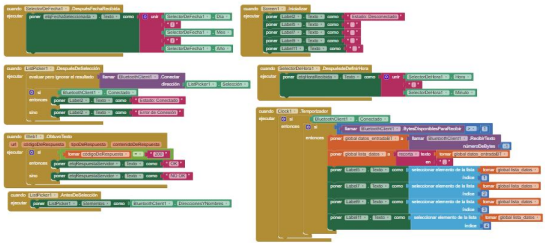

Fig. 6: Screen 2 programming blocks for data acquisition from Arduino

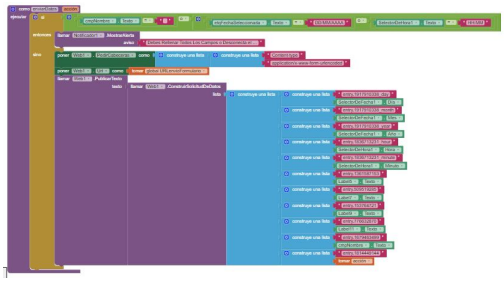

Fig. 7: Screen 2 programming blocks for form filling

app and the device, in order to take the measurements from the Bluetooth module on arduino UNO microcontroller(Figure 6) and save it on a Google Sheet through the use of a Google Form (Figure 7).

The third screen allows the user to consult the measures taken and stored on the database or Google Sheet, detailed by signal, date and time(Figure 9) .

IV. Results

The device consists of a SPR sensor, HR sensor and Body temperature sensor to an arduino UNO microcontroller (Figure) and a Bluetooth module to transmit the signals to a mobile App.

The measurements were performed in a non-diabetic person, who uses our device and through the application a database was created where the data was stored. The results are summarized in the table where we can see the different measurements of our device. The values that we can see in the table I are heart rate, skin potential, temperature, the prediction of glucose

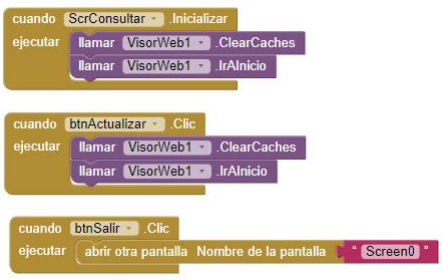

Fig. 8: Screen 3 programming blocks to visualize the Google Sheets with data recorded

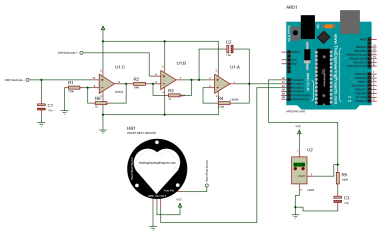

Fig. 9: Breadboard simulated using Proteus application of the GlucoPhy device (SPR, HR and Temperature sensors)

(a) Principal Screen

(b) Measurements screen

(c) Consult screen

Fig. 10: Application Screens

levels obtained by Glucophy and the glucose levels obtained by a commercial glucometer. This table also shows the error of the measurements, which is in the range of 20% to 30%.

Based on the information obtained in the table we can see that glucose is related to changes in skin potential so that we can clearly see that when SP values decrease, glucose levels also decrease and also when SP values increase, glucose levels increase. This shows the relationship that exists between SP and glucose levels, showing us a direct proportionality.

V. Discussion

The hardware we have designed is adaptable to several models for glucose prediction because it presents the measurement of 3 types of physiological signals. For this first approach we used the model by Saad et al. [18] The measurements were obtained by using sensors with arduino and sent to the application and from algorithms we obtained each of the values presented in the table I. Although the model we used is a linear model that only takes into account the SP

HR	SP	T	BGL(Glucophy)	BGL(real)	Error
59.1	1.92	28.84	6.35	5.11	0.24
61	1.83	29.77	6.57	5.11	0.29
51.8	1.62	25.28	7.05	5.61	0.26
51.1	1.63	24.94	7.04	5.61	0.25
50.4	1.61	24.6	7.07	5.61	0.26
50.6	1.62	24.69	7.05	5.61	0.26
59.8	1.78	29.18	6.67	5.27	0.27
54.2	1.72	26.45	6.81	5.83	0.17

TABLE I: Measurement of the device

values, this system was already prepared to adapt to models where the temperature and characteristics obtained from a photopleistogram signal are used.

Studies have shown that there is a relationship between changes in physiological signals and glucose levels. Now compared to other measurement methods, it presents an advantage because it is not invasive, it can allow continuous monitoring, it is economical and it allows us to transfer information to a database that is managed by the application. On the other hand, the model has an advantage over other models in that it only requires a single physiological signal (SP). However, due to its low accuracy it is weak to regression models that are based on HRV time and frequency domain features obtained from the use of PPG or ECG signals. [12] [20] [21]

In fact, this system presented an average error of 25% in the BGL measurement, which makes sense at a correlation of 0.67 [18]. This shows that it is not a very accurate model, in contrast to the model by Habbu et al [7]. who obtained a correlation of 0.95 in the BGL prediction with PPG signals.

VI. Conclusions

The ability to measure glucose noninvasively and in real time provides a number of advantages and value to consumers. The system presented in this paper presents a hardware design that is capable of adapting to various glucose prediction models including the use of SP-based models, PPG-based models, and combined models. The current design can be improved and taken to a commercial product which through the application can monitor glucose levels and store them in a database, being able to generate control and alarms. In addition, the system is cost-effective compared to invasive systems.

VII. Future Works

Future work includes: improving the system and making it more comfortable, reducing the circuit, improving the prediction algorithm by developing a prediction model based on parameters of the 3 physiological signals using Machine Learning, improving the application and providing a better user interface that allows sharing the results between the patient and the medical expert.

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