Early Detection of Hypoglycemia Events based on Biometric Sensors Prototyped on FPGAs

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Abstract. Diabetes is a chronic disease that requires continuous medical care and patient self-monitoring processes. The control of the glucose level in blood is a task that the patient needs to perform to prevent hypoglycemia episodes. Early detection of hypoglycemia is a very important element for preventing multi-organ failure. The incorporation of other biomedical parameters monitoring, combined with glucose levels can help to early detect and prevent those episodes. At this respect, several e-health platforms have been developed for monitoring and processing vital signals related to diabetes events. In this paper we evaluate a couple of these platforms and we introduce an algorithm to analyze the data of glucose, in order to anticipate the moment of an hypoglycemia episode. The proposed algorithm contemplates the information of several biomedical sensors, and it is based on the analysis of the gradient of the glucose curve, producing an estimation of the expected time to achieve a given threshold. Besides, the proposed algorithm allows to analyze the correlations of the monitored multi-signals information with diabetes related events. The algorithm was developed to be implemented on an FPGA-based SoC and was evaluated by simulation. The results obtained are very promising and can be scalable to further signals processing.

Keywords: e-health Platforms, FPGAs, Biometric Sensors, Continuous Glucose Monitoring, Diabetes.

1 Introduction

The International Diabetes Federation estimates that 387 million people worldwide suffered from diabetes in 2012 and it is expected an increase of 215 million people more by 2035 [1]. Diabetes is a chronic illness that occurs when the pancreas is no longer able to produce insulin (or not enough amount), an hormone that acts letting glucose that we obtained through the ingestion of carbohydrates, to pass from the blood towards the cells in the body to produce energy. Consequently, the diabetic patient presents abnormally raised glucose levels in blood that, in absence of an effective treatment, may produce important damages to various organs or even the death.

The control of its glucose level in blood is a basic task that a diabetic patient needs to perform several times per day in order to help adjusting the amount of insulin to be injected. The most basic way consists in piercing the skin (normally a finger) using an electronic device called glucometer that extracts a small blood sample and then applies to a chemically active disposable test-strip, able to read the concentration of glucose. However, according to [7], this approach presents limitations with regard to the accuracy and specificity as well as the need of sticking several times per day. Advances in microelectronics enable the Continuous Glucose Monitoring (CGM) [12], a technique that determines glucose levels in the interstitial fluid on a continuous basis. To this end, a glucose sensor is implanted under the skin of the patient for a few days, normally between 3 and 7 days. This sensor normally operates by transmitting every a few minutes the average of the concentration of glucose of the samples towards a nearby non-implanted receiver, which displays on a small screen both the actual measurement and the curve of glucose levels along the time to see rising and falling trends. In order to describe more precisely the current clinical state of the diabetic patient and to be able to anticipate diseases as are the hypoglycemias and hyperglycemias (values abnormally low and high of glucose, respectively), the monitoring of additional parameters is being progressively incorporated. As described in [2], the heart rate variability combined with the monitoring of the glucose levels may increase the time of forecasting of hypoglycemias, yielding a lead time of 22 minutes as compared to the CGM device. The work presented in [6] reveals significant inverse changes of the ECG parameters (e.g. QT, PR, RT and TpTe intervals) upon the occurrence of an hypoglycemic process. Therefore, the real-time processing of more and more signals, corresponding to vital signals whose values are altered in presence of hypo- and hyperglycemia events such as the heart rate, sweeting, and blood pressure, could increase the time interval given by the moment of detection of the event and the moment of its potential occurrence. It is important to stress that such time of anticipation could result critical for implementing the medical actuation required to avoid the risk. Given the potentially high number of signals to be processed and the importance of the processing time, FPGAs are very adequate for the execution of real-time medical applications where the analysis and study of signal patterns behavior are necessary. The internal structure of FPGAs allows parallelizing the execution of several algorithms using simultaneous instantiation of the corresponding component, feature that is very useful to analyze the correlation of events produced in a determined signal, in correspondence with the behavior of the rest of them. Besides, FPGAs allow to develop customizable high speed data acquisition systems to create multi-signals processing systems.

In this work we evaluate a couple of commercial e-health platforms that enable the continuous monitoring of vital parameters. e-health platforms integrate several biometric sensors, a microcontroller, and some sort of communication radio to transmit the readings towards an external receiver. By using biometric sensors, we propose an algorithm for improving the detection of hypoglycemias and we implement it on an FPGA with the purpose of comparing its perfor-

mance against alternative e-health platforms and evaluating its suitability for implementing medical algorithms. The rest of the paper is organized as follows. After reviewing the related work we describe in Section 3 the medical parameters to be monitored in presence of diabetes and in Section 4 we propose and algorithm for hypoglycemias detection. Section 5 shows the results of testing two e-health platforms and the evaluation of the proposed algorithm on an FPGA. Finally, in Section 6 we draw the conclusions and future research work.

2 Related Work

CGM enables to predict the risk of hypo- and hyperglycemia and to adjust better the administration of insulin [4]. However, most of the current CGM devices are invasive (since they require accessing blood or interstitial fluid), expensive, they require still calibration by finger sticks (several times per day) for optimal glucose sensor accuracy, and their lifespan is limited to just a few days. Three examples of certified, still invasive CGM sensors currently used by diabetic patients are *ipro*, *abbot*, and G4/G5 Dexcom series. *ipro* kit is composed of a sensor implanted under the skin and an *ipro recorder* that receives and stores the readings of the sensor. A reading is sent from the sensor towards the receiver each 5 minutes, which represents 288 daily readings. The *ipro recorder* is not able to communicate with a smartphone; instead of that, after as much 6 days, the sensor must be removed and replaced, and data must be downloaded from the recorder for its interpretation. The *abbot* system comprises a CGM sensor and a reader device able to scan the sensor when located at distances from 1 up to 4 cm. This CGM sensor measures the glucose level each 15 minutes, which represents 96 daily readings. In turn, the glucose sensors series from Dexcom are especially indicated for children from 2 years. The novelty of this system regarding to the previous ones, is that the sensor is able to transmit each reading via Bluetooth towards a smartphone, which enables also its visualization. The next generation of CGM includes a small pump of insulin that is connected to a needle subcutaneously implanted under skin; this mechanism is able to supply insulin upon the clicking of a button, at discrete time to reduce the glucose concentration or continuously to maintain the basal rate [3], based on the readings from the glucose sensor.

The research in microelectronics and MEMS technology is focused on providing still continuous monitoring but through pain-free, non-invasive devices that avoid the necessity of piercing the skin. This technique is known as Non-invasive Glucose Monitoring. The main weakness of non-invasive sensors is their accuracy, which is still far from achieving the precision level of finger sticks. In the last few years have appeared non-invasive devices to measure the glucose levels, as GlucoTrack, that provides a sensor that clips to the patient's ear lobe and uses an algorithm to compute the glucose level, or Glucowise, which may be positioned between the thumb and forefinger or at the earlobe. Wearable computing also enables the continuous monitoring of parameters related to health and physical activities. Wearable computing is intended to be continuously available, observable, and controllable by the user, but does not need its attention

and do not constraint its movements [5]. Wearable computers are implicit to the body, they are worn (not carried) comfortably on our clothes or as watches, glasses or lens, and are aimed at sensing both vital signals as environmental parameters through multiple sensors. In this sense, the next generation of non-invasive glucometers trends to be devices worn, able to continuously read the glucose level and communicate the readings wirelessly towards a smartphone or computer. A first prototype of these devices are iWatch (Apple) and Google's smart contact lens. Continuing at the experimental level, open e-health platforms are proliferating as an effective mean mainly oriented to assist developers and researchers in the evaluation of innovative algorithms for predicting, detecting, and tracking illnesses. They are not conceived for the monitoring of critical patients since they do generally not have medical certifications. An e-health platform enables the body monitoring through a rich set of biomedical sensors, as well as providing the capabilities of processing, storing, and communication. e-health Sensor Shield [8] is a PCB designed to connect nine sensors: patient position (accelerometer), glucometer (invasive), body temperature, blood pressure (sphygmomanometer), pulse and oxygen in blood, airflow (breathing), sweating via galvanic skin response (GSR), electrocardiogram (ECG), and electromyography (EMG). This shield can be connected to both Arduino and Raspberry PI platforms, which provide capabilities of processing and transmission of data (e.g. Wi-Fi, GPRS, Bluetooth, 802.15.4). The medical information collected can be used to monitor in real time the state of a patient and for medical diagnosis, yielding a large set of different medical applications. A limitation of the e-health Sensor Shield is that not all sensors can work together. The BioMedical Development Kit [10] from BITalino, is an easy-to-use and low-cost toolkit to learn and prototype applications using body signals. This consists of a PCB with a microcontroller, Bluetooth 2.0, a Li-Po Battery 320mAh, a LED actuator and ECG, EMG, Electrodermal Activity, accelerometer and light sensors, all of them can be connected to the board through USB ports.

On the other hand, the inherent parallelism to FPGA architectures results very appealing for the implementation of data-intensive medical applications. For example, the work presented in [9] implements on an FPGA a discrete-time inverse neural controller to regulate the glucose level in diabetic patients, thus providing a first step to develop an artificial pancreas.

3 Early Detection of Hypoglycemias

The system that we are proposing has as a primary goal the early detection of hypoglycemias. Our proposal applies to diabetic patients subject to a therapy consisting in the continuous monitoring of their glucose level in blood (glycemia), which is the most relevant evidence for the diabetic. In our system model, the diabetic patient monitors its glycemia by means of a CGM device, which measures the glucose level in blood in a continuous basis. In particular, the values of glycemia before and two hours after breakfast, lunch, and dinner are especially relevant. The evidence that reports on if the patient is controlling its glycemia

well is the glycosylated hemoglobin (also known as HbA_{1c}), that represents the average glycemia during the last 90-120 days and that is obtained through a blood test in the laboratory. In addition to this, some diabetic patients present risk factors for the illness as are the hypertension and the overweight. Hypertension is controlled through blood pressure tests, which deliver two values p_1, p_2, where p_1 is the systolic pressure (the pressure when the heart beats) and p_2 is the diastolic pressure (the pressure when the heart muscle is resting between beats and refilling with blood). In turn, the existence of overweight is determined by means of the Body Mass Index (BMI), that represents the relative size of an individual and it is computed as $BMI = \frac{weight}{height^2}$, where *weight* is expressed in kilograms and *height* in meters. It follows that the lifestyle, particularly diet and practice of sports, impact on BMI. Diet is a critical part of the treatment of any diabetic patient with overweight, intended to take care of the ingestion of calories, fats, and carbohydrates, including the uniform distribution of calories among meals. Physical exercise is indicated in most of the cases but mainly in presence of overweight. The heart rate provides the number of contractions of the heart per minute, and it increases with the intensity of the exercise. To this regard, during the physical activity of the patient, it would be useful to monitor its heart rate variability to avoid that it exceeds the maximum heart rate (HR_{max}), which can be computed by taking into account the gender and the age of the patient according to the Haskell and Fox's equation: HR_{max}=220-`age` (in men) or HR_{max}=226-`age` (in women). Note that HR_{max} is the theoretical maximum heart rate that can be achieved without harming the health under optimal physical conditions. Note also that exercise usually lowers blood glucose level; therefore, the monitoring of the glucose level during the physical activity is key for hypoglycemias detection.

We consider two symptoms more that generally accompany the first stages of hypoglycemia: sweating and trembling. Sweating occurs all over the body but mainly in face and hands, and it may be associated to an increase of the body temperature, which should be also monitored. A sort of slight trembling may appear in fingers and hands, and it is generally only observed by the person that experiences it without being visible to other persons. There exist many other symptoms associated to the early stages of hypoglycemia such as hunger, weakness and fatigue, headache or impaired vision. For our purpose, we have focused on those parameters associated to hypoglycemias that can be measured through the e-health platforms that we have available in our laboratory. Table 1 presents the values of reference and imbalances for the parameters considered.

4 Algorithm for Hypoglycemias Detection

Let us consider an e-health platform for the continuous monitoring of glucose in conjunction with the monitoring of heart rate, blood pressure, temperature, position, sweating, and trembling. Thus, the platform integrates $n = 7$ sensors named $s_0, \ldots, s_6$, each one is sampling a vital sign at a suitable periodicity: s_0 is a CGM sensor, s_1 is a heart rate sensor, s_2 is a tensiometer that measures the

Parameter	Normal Values	Abnormal Values	Observations
Glycemia	$70 - 100$ mg/dl	–	No diabetes (fasting)
	< 140 mg/dl	–	No diabetes (after eating)
	$100 - 125$ mg/dl	–	Pre-diabetes (fasting)
	$140 - 199$ mg/dl	–	Pre-diabetes (after eating)
	–	≥ 126 mg/dl	Diabetes (fasting)
	–	≥ 200 mg/dl	Diabetes (after eating)
	–	≤ 70 mg/dl	Hypoglycemia
	–	≥ 200 mg/dl	Hyperglycemia
HbA_{1c}	$4 - 6\%$	–	–
	–	$\geq 6.5\%$	Bad control of glycemia
BMI	$18.0 - 24.9$	–	No overweight
	–	$25.0 - 29.9$	Overweight
	–	≥ 30.0	Obesity
HR	$\leq (60 - 80\%)HR_{max}$	$> HR_{max}$	–
p_1	$90 - 119$ mm Hg	–	Systolic Pressure
	–	$140 - 159$ mm Hg	Stage 1 Hypertension
	–	$160 - 179$ mm Hg	Stage 2 Hypertension
p_2	$60 - 79$ mm Hg	–	Diastolic Pressure
	–	$140 - 159$ mm Hg	Stage 1 Hypertension
	–	$160 - 179$ mm Hg	Stage 2 Hypertension

Table 1. Normal and altered values for some vital parameters related to diabetes.

blood pressure (systolic and diastolic), s_3 is a body temperature sensor, s_4 is an accelerometer that detects the patient's position (fowler's, prone, supine, and recumbent) and that is useful to detect falls, s_5 is a GSR sensor that measures the electrical conductance of the skin, which varies with its moisture level and s_6 is an EMG sensor, which measures the muscle activation via the electric potential. All these sensors are available in the e-health platforms described in Section 2. We also consider the age, the gender, and the weight and height of the patient as fixed parameters which, therefore, do not need to be continuously monitored through a sensor; similarly, HbA_{1c} is a parameter that could be estimated by computing the average of the values of glucose.

Each sensor is provided with a sampling frequency f_i, which corresponds to the rate of readings taken by sensor i, initially defined as $f_i = 300$ seconds $\forall i \in [0, n)$. These frequencies could be adjusted depending on the variability of their values along a day and the necessity of register them for diagnosis purposes. Each sensor is also provided with a maximum threshold denoted as $\max_i$. By taking the series of readings from the sensors along the time as an input, we propose an algorithm for analyzing the data of glucose in order to anticipate the moment of time of the occurrence of an hypoglycemia event. This analysis is based on the computation of the slope of the curve drawn by the glucose level in blood along the time. At each sampling period, a value of each sensor denoted as v_i is obtained, for all $i \in [0, n)$. Let us also define $v_0(t)$ as the glucose reading at time t and α as the maximum angle drawn for the segment $\overrightarrow{AB}$ ($A = v_0(t)$, $B = v_0(t + 1)$) with the horizontal axis. Thus, for any two consecutive readings $v_0(t)$ and $v_0(t+1)$ the slope of the curve is $m = \frac{dv_0}{dt} = \frac{v_0(t)-v_0(t-1)}{t-(t-1)}$ and by using simple geometry its angle is $\theta = \arctan m$. The slope is positive (ascending) iff

Algorithm 1 Hypoglycemias Detection Algorithm

Require: v_i is the reading of sensor i at time t, $f_i = 300$ is the sampling frequency $\forall i \in [0, 6]$; $\max_i$ is the threshold for sensor i $\forall i \in [1, 6]$
Require: $\min_0 = 70$ is the minimum threshold for s_0; α is the maximum angle
Ensure: T: the estimated anticipation time of a potential hypoglycemia

```
G = 0    %initial value of glucose
F = f_0    % the frequency for sampling the glucose sensor
threshold = min_0 ×1.25    % a threshold for the glucose value
loop
  % At each sampling period
  if(G == 0) then G = v_0; break;
  m = (G−v_0)/f_0; θ = arctan(m); T = (f_0×(v_0−min_0))/(G−v_0); G = v_0
  case 0: (θ < α)
      break;          % Normal state
  case 1: (θ < α) ∧ (v_0 ≤ threshold)
      initiate sampling s_1 ... s_6          % Low glucose
      if (v_i ≥ max_i), 1 ≤ i < n then return T      % Alert hypoglycemia
  case 2: (θ ≥ α)
        f_0 = F/3          % Pre-hypoglycemia state
        initiate sampling s_1 ... s_6
        loop
          m = (G−v_0)/f_0; θ = arctan(m); T = (f_0×(v_0−min_0))/(G−v_0); G = v_0
          if(θ ≥ α) then f_0 = F/3
          if(θ < α) ∧ (m > 0)then f_0 = F/2    % Risk factors state
          if (m ≤ 0) then F = f_0; stop sampling s_1 ... s_6; break
          if (v_i ≥ max_i), 1 ≥ i < n then return T      % Alert hypoglycemia
        end loop
end loop
```

$m > 0$ and it is negative (descending) iff $m < 0$. If $\theta < \alpha$ (θ, α are expressed in degrees) the slope of the curve is under the threshold and glucose keeps within the normal levels; otherwise, the slope of the curve is above the threshold and, therefore, glucose level is falling more quickly than recommended. Note that it could be still possible a descending slope while $\theta < \alpha$ holds, so glucose is falling but not dramatically for our purpose. The pseudo-code is shown in Algorithm 1.

The algorithm enters into a loop that starts to sample only the glucose sensor s_0 each f_0 and keeps in this state until two possible events occur: 1) v_0 drops under a threshold defined slightly above $\min_0 = 70mg/dl$ (which is the minimum value of glucose to be considered hypoglycemia) and 2) the angle θ is larger or equal than the maximum angle α. In both cases, the glucose level is descending with the time (in the second case it falls at a faster pace than in the first case), so in both cases the algorithm starts sampling the rest of sensors $s_1 \dots s_6$ to monitor the symptoms of a possible hypoglycemia. In the first case, if some value v_i exceeds the allowed threshold (i.e. $v_i > \max_i, i \in [1, n)$) then, an alert is generated to warn the medical team about a potential hypoglycemia and the algorithm returns the estimated time T to achieve $\min_0$ while the slope m is kept.

The second case occurs when two consecutive values of glucose form an angle $\theta \geq \alpha$, which means that is dropping quickly. The algorithm adjusts the sampling frequency for the glucose sensor to $f_0 = \frac{f_0}{3}$ in order to be able to anticipate the risk detection. As in the first case, if some value v_i exceeds the allowed threshold an alert is immediately generated. Otherwise, if the slope is still lower than 0 but at slower pace ($\theta < \alpha$) then the reading frequency for the glucose sensor is updated to $f_0 = \frac{f_0}{2}$. Under the event of a glucose value larger than the previous one, i.e. drawing an ascending slope ($m \geq 0$), the algorithm returns to the initial state. Figure 1 represents the different cases described above.

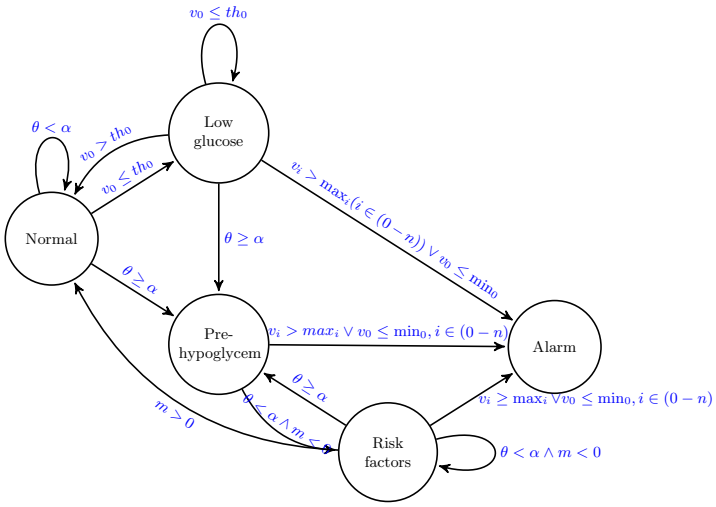

Fig. 1. State transition diagram for the cases considered in Algorithm 1.

5 Evaluation

This section presents the evaluation of our approach. We first test the e-health sensor shield and BITalino platforms in order to compare the results that are obtained from equivalent sensors in both platforms. Second, we evaluate by simulation our algorithm on an FPGA-based SoC. For the work presented here a development platform based on SmartFusion II FPGA with Arduino compatibility has been used. This compatibility allows to connect the sensing platform to the FPGA to perform the required computation. Although the evaluated platforms are based on a microprocessor such Arduino, ARM, the incorporation of reconfigurable logic allows to develop hardware versions of different algorithms for signals processing that could require improved computational performance. The next subsections describe the evaluation method and results.

5.1 Testing e-health Sensor Shield and BITalino Platforms

We have written a program to collect data from the sensors in e-health Sensor Shield connected to Arduino. This program enters into a loop where in each iteration the pulseoximeter, temperature, GSR, accelerometer, and airflow sensors are sequentially read. Since ECG and EMG sensors cannot be used simultaneously, we proceed to implement different versions of the program, one to read ECG signal and the other one to read the EMG signal. The glucometer and the sphygmomanometer devices can neither work together; they are not sampled as a result of the invocation of a program's function but instead they work autonomously and just transmit data to Arduino (number of measures stored in the device, and date and time associated to each value of glucose/blood pressure sample) when they are requested via the appropriate reading function. Thus, in each loop iteration we ask for new measures of glucose/blood pressure to avoid overflow the output buffer. Accelerometer and blood pressure sensors were sampled only once since they do not (or almost not) suffer variations along the time frame. Glycemia was not monitored in this experiment (see next subsection for details). The test demonstrated that the ECG, temperature, oxygen saturation, and blood pressure sensors seem working accurately for purposes of non-critical monitoring. Additionally, since EMG sensor measures the muscle intensity, the test proved that the highest values coincide with some action done by the carrier of the sensor. GSR conductance voltage and airflow values should be compared against another reliable device. However, the position sensor revealed incorrect results in most of the samples as it is also stated in [8]. The average time taken by each loop iteration is 318.8 ms. In turn, BITalino provides a software that makes most of the work for us, letting to sample the sensors and visualize the results in a real-time via a user-friendly interface on the PC or smartphone. The sampling program executes on Arduino and BITalino platforms during a time frame of 10 minutes and by using a sampling period of 30 seconds, which means that 20 readings per sensor and per individual were collected. The tests were developed with help of three healthy volunteers in seated position.

As an example, we show in Figure 2 the values of ECG and EMG collected on the Arduino platform. ECG parameters are, according to [6], altered in presence of hypoglycemia. ECG and EMG results for the same persons obtained from BITalino platform are presented in Figure 3. As observed, the sampling frequency of this platform is much higher than the provided by Arduino. Both platforms may potentially support an algorithm for hypoglycemia detection based on the continuous monitoring of ECG parameters together with the glucose levels.

5.2 Simulation of the Algorithm on an FPGA

We have developed a prototype in VHDL to be deployed on any FPGA. Our prototype uses two data bus for input/output standard communication and an input signal for each sensor $s_0, \ldots, s_6$. Our prototype is able to simulate the algorithm described in Section 4 by taking the CGM input data from real patients. In our simulations, the execution time of the algorithm is 6 cycles (in the

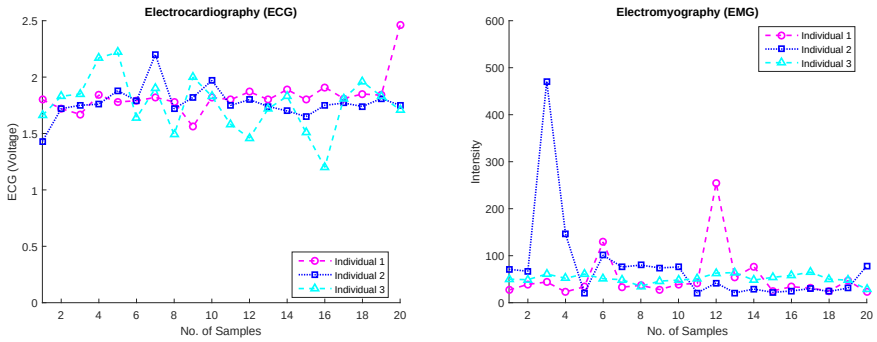

Fig. 2. ECG (on the left) and EMG (on the right) samples obtained from Arduino.

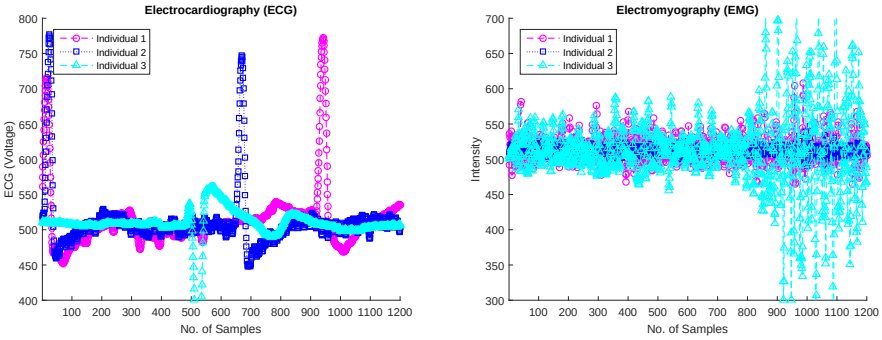

Fig. 3. ECG (on the left) and EMG (on the right) samples obtained from BITalino.

worst case), which means that the simulated platform (SmartFusionII) working at 100MHz delivers a time of approximately 60 microseconds.

In order to make more realistic simulations we have taken the data of CGM of three diabetic patients described in [11] that suffered hypoglycemia episodes. For our purpose we fix α=[-5,-8] (note that a negative angle corresponds to a $360° + \alpha$ angle). Table 2 shows the expected time T in minutes and the slope m for each one of the three patients and for each state transition (i.e. each slope variation) before achieving the minimum value (70 mg/dl). Figure 4 shows the best results for patient 1 (left), patient 2 (center) and patient 3 (right). The axis x is showing the number of samples and the axis y represents the glucose levels. Figures on the left and on the right correspond to transitions from `Normal` to `Low` state, that occurs when the threshold 88 mg/dl (e.g. 1.25% of 70 mg/dl) is achieved (red line), while the figure in the middle shows the case when the algorithm transits from `Normal` to `Pre-hypoglycemia` state because $\theta \geq \alpha$, that occurs for glucose levels under 70 mg/dl (blue line). Times are provided when the threshold is achieved (figures on the left and right) or when $\theta \geq \alpha$ (figure in the middle). The best case occurs if in the moment of detection the glucose is far from the threshold and θ is slightly above α.

	α=-5		α=-6		α=-7		α=-8	
	T	**m**	**T**	**m**	**T**	**m**	**T**	**m**
Patient 1	9.4	-0.3	28.3	-0.3	28.3	-0.3	28.3	-0.3
	1.4	-0.9	1.4	-0.9	1.4	-0.9	1.4	-0.9
Patient 2	23.9	-0.9	23.9	-0.9	23.0	-0.9	23.9	-0.9
	700	-0.3	700	-0.3	700	-0.3	700	-0.3
Patient 3	95	-0.1	95	-0.1	95	-0.1	95	-0.1
	30	-0.1	30	-0.1	30	-0.1	30	-0.1

Table 2. Estimated time (T) in minutes for an hypoglycemia episode and gradient (m) of the curve for different values of α.

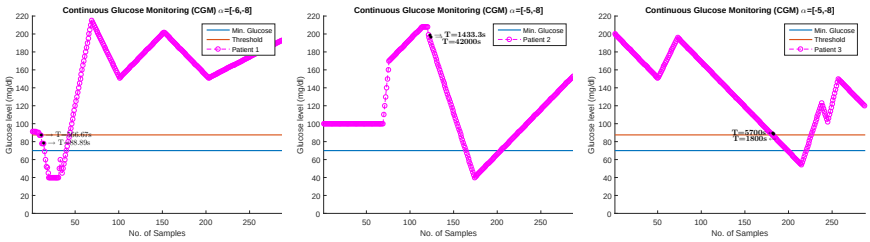

Fig. 4. CGM curves and estimated time for hypoglycemia for different values of α.

6 Conclusions

The continuous monitoring of variables associated to medical disorders by means of biometric sensors, integrated into e-health platforms and into wearable devices, enables the design of algorithms able to detect the potential occurrence of risk events based on the correlation of data series collected from the sensors. Anticipating the early detection of risks is of utmost importance to increase the time to implement medical actions that avoid critical situations. Precisely with this motivation we have firstly tested two commercial e-health platforms (e-health Shield Sensor/Arduino and BITalino) to show their suitability and weaknesses for biomedical signal monitoring and data acquisition for medical applications. Secondly, we have proposed an algorithm for early detection of hypoglycemias that in this first stage was simulated on an FPGA, in order to investigate how can be implemented taking into account the correlation of the signals obtained with the aforementioned platforms. The algorithm is based on the analysis of the gradient of the glucose curve and estimates the expected time to achieve a given threshold. The simulation takes as input the glucose levels of diabetic patients that suffered hypoglycemias. The results show that our algorithm may effectively predict their hypoglycemias episodes anticipating the time of its occurrence (from several minutes to hours depending on the gradient considered). The execution time of our algorithm on an FPGA is several orders of magnitude lower than the time delivered by Arduino.

As future works we plan to improve the anticipation time of our algorithm by investigating the correlation of the data series collected from other sensors (e.g. heart rate, ECG, sweating) with regard to the glucose levels, since they are

measuring recognized symptoms of hypoglycemia. We also plan a more exhaustive evaluation that takes as input data obtained from real diabetic patients and covers a wider spectrum for the values α and θ.

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