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Smart Wristband with Integrated Chemical Sensors for Detecting Glucose Levels using Breath Volatile Organic Compounds

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ABSTRACT

This paper presents a microcontroller-based solution to classify blood glucose levels using acetone and ethanol breath volatile organic compounds. Two metal oxide semiconductor-based chemical sensors able to detect acetone and ethanol at parts per million concentrations were used. The sensors were tested in a controlled setup with humidified air spiked with acetone and ethanol, mimicking human breath corresponding to low and high blood glucose groups. A support vector machine algorithm was trained and implemented in a microcontroller. In a real time-time test, the trained algorithm classified low and high blood glucose groups with 97% accuracy. Subsequently, a smart wristband prototype that integrates the two sensors was developed. An Arduino-based wearable microcontroller platform was used for its small formfactor and a low-power operation. The wristband is enclosed in a 3D printed housing and powered by an onboard 3.7 V 500 mAh rechargeable Li-ion battery. A smartphone app communicates with the wristband through Bluetooth, allows data visualization, and saves data in the cloud. The presented work makes a significant contribution towards the development of a wearable device for detecting blood glucose levels from a patient's breath.

Keywords: Smart wristband, wearable sensors, smart sensing systems, sensor data analysis, blood glucose level, diabetes, volatile organic compounds

1. INTRODUCTION

It is projected that by 2030, more than 15% of US population will have diabetes and the treatment of diabetes will cost over 600 Billion US dollars in a year [1-3]. With the cases of diabetes increasing every year, the presented smart wristband provides a non-invasive tool for monitoring blood-glucose (BG) levels. Self-monitoring and measurement of BG levels is not new. Currently, BG levels can be readily measured using a finger-prick glucometer with an accuracy of 95% or higher [4]. Patients needing close monitoring of BG levels use continuous glucose monitoring devices [5]. Children with type-1 diabetes are at risk of going into both hypo and hyper-glycaemia, often times without noticeable symptoms. If not treated in a timely manner, the hypo and hyper-glycemic episodes can cause short as well as long-term health complications. For this particular reason, many parents of children suffering from type-1 diabetes have sought the help of dogs that are trained to sniff out hypo and hyper-glycaemia when they are around a patent [6-7]. These canines, known as Diabetic Alert Dogs or Diabetic Assist Dogs (DADs), are trained using breath and perspiration samples of a patient collected when the patient is undergoing a hypo or hyper-glycemic episode. Because DADs are able to continuously monitor possible hypo and hyper-glycemic episodes, parents have been reported to have decreased wariness and improved physical activates for their children [8]. Studies looking into the methods of training these dogs have shown that DADs detect diabetes using volatile organic compounds (VOCs) released through patient's breath and perspiration [9]. Furthermore, studies analyzing collected breath and perspiration samples have shown that there is a definitive link between VOCs in the breath and blood glucose levels [10-12]. Thus, there is clinical potential for detecting blood glucose levels using exhaled VOCs non-invasively and passively and, potentially, faster and at a lower cost. Silicon tungsten oxide sensors for acetone as a means to estimate BG level is presented in [13]. A platinum functionalized tungsten oxide sensor for sensing acetone in exhaled breath is presented in [14]. Nanotubes and nanoparticles-based sensors for detecting acetone from breath are reported in [15, 16].

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This paper presents a wearable passive glucose monitoring device using acetone and ethanol in exhaled human breath. The VOCs were selected based on the published work on breath VOCs and their correlation with diabetes [17-20]. Commercially available metal oxide semiconductor (MOS)-based VOC sensors were integrated into a sensing system. We tested the sensors in humid air spiked with acetone and ethanol. The sensor data was used to train a support vector machine (SVM) algorithm and implement in a microcontroller. A smart wristband integrating the sensor array was developed and enclosed in a 3D printed housing. The wristband communicates with a smartphone App and logs data into the cloud. The design procedure, test methods and results, and developed systems are presented and discussed.

2. METHODS

2.1 Volatile Organic Compounds

We reviewed published data on breath compound analysis and VOCs linked to blood glucose levels [10-20]. We found that there is quite a variation in reported VOCs that are linked to diabetes and their correlated concentrations. We looked for VOCs that were consistently reported across publications and that the literature generally agreed on correlations of the VOC concentrations and associated blood glucose levels. We found that acetone, ethanol, methanol, and methyl nitrate fit the profile. Based on our laboratory laminations and time constraints in acquiring and working with the VOCs, we chose acetone and ethanol as the two VOCs for further test and analysis. Given the number of published work that used just acetone or acetone and ethanol, and also because of controlled manner of our experiment, we were confident that the two VOCs would be adequate to produce classification results with good accuracy. We divided the blood glucose levels in two groups; high: representing reported blood glucose levels of 125 mg/dL and higher, and low: representing blood glucose levels of 100 mg/dL or lower. The associated concentrations of the VOCs are as follows; low BG level: acetone 1-3 parts-per-million (ppm) and ethanol 0-20 parts-per-billion (ppb), and high BG level: acetone: 5-7 ppm and ethanol: 35-50 ppb. These signatures were used for all subsequent tests.

2.2 Hardware

Two commercially available metal-oxide-semiconductor based chemical sensors that have been reported to detect the selected VOCs at the concentration levels indicated above, but with different sensitivity levels, were selected [21-23]. The sensors are packaged in a metal housing with a meshed opening for VOCs to enter the housing and reach the sensing element (Fig. 1(a)) [23]. Initial characterization tests to learn the response behavior of the sensors were conducted with acetone. The sensors have four pins, two for sensing element and two for powering heating element as the sensors need to be warmed up to achieve the indicated sensitivity levels. Each sensor was connected in series with a resistor to create a voltage divider, sensor connecting to the positive power rail (VCC) (Fig. 1 (b)) [23]. For both sensors, the resistance decreases when VOCs are introduced. Thus, the voltage reading from the voltage divider, VOUT in Fig. 1(b), increases when a VOC is introduced. To choose the voltage divider resistance, each sensor was separately tested by introducing a low and high VOC signature and measuring the resistance of the sensor. Each divider resistance was chosen to be about an average of the two measured resistance values. Arduino Mega microcontroller (Fig. 2(c)) was used for reading the sensor data and, subsequently, pushing to a computer via serial print, where the data was saved as a comma separated value (CSV) file.

2.3 Test Setup and Flow Control

An in-house developed test setup is shown in Fig. 2. The setup consists of three air-sealed glass jars (chambers) connected in series. The air flow was controlled using an airflow control valve between the setup and the air tank. Ultra-pure air with 80% nitrogen and 20% oxygen was used. The air was bubbled through de-ionized water to introduce humidity akin to the humidity of exhaled breath. Tests conducted separately have shown that the humidity of air when bubbled through water reaches close to 100%. Among the three chambers, the VOCs were introduced in the first chamber, sensor array was placed in the second chamber, and the third chamber served as a VOC trap. A series of tests for various flow rates and timing for introducing the VOC and reading of the sensors were conducted. Based on the results from the tests, the timing and flow rates shown in Table 1, were found to be optimal, and were used for subsequent tests. As shown in the table, the tests were conducted in the following sequence. The system was cleared for five minutes at 1.5 L/min. The airflow valve was closed and the test VOCs were introduced in the first chamber (VOC Chamber) through a small opening and a syringe with a micro needle. The amount of a liquid VOC was determined based on its desired concentration and the molecular weight of the VOC compared to the chamber size. The opening was closed promptly after the introduction of the VOC. The valve was kept closed for 60 seconds to allow the VOC to evaporate in the chamber. The evaporated VOC was carried to the second chamber containing the sensor array (Sensor

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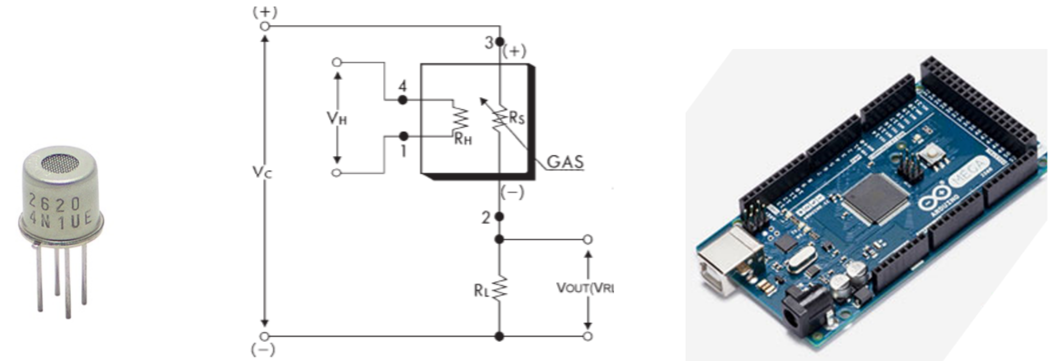
Chamber) by opening the valve for 45 seconds at 0.5 L/min air flow. The sensor array connects to a microcontroller which reads the sensors and feeds data to the PC. The sensor data collection began taking a sample every five seconds. The valve was kept closed for another five minutes fifteen seconds, following which the valve was opened at 1.5 L/min for three minutes to clear the VOCs from the system, completing one test cycle.



(a) (b) (c)

Figure 1: (a) A Figaro 2620 metal oxide seminconductor VOC sensor [23]. (b) A connection to the four pins of the sensors, two pins connecting to an internal heating element and remainig two pins to the sensing element. The sensing element is connected in seires with a load resistor (R_L) [23]. (c) An Arduino Mega microntroller.

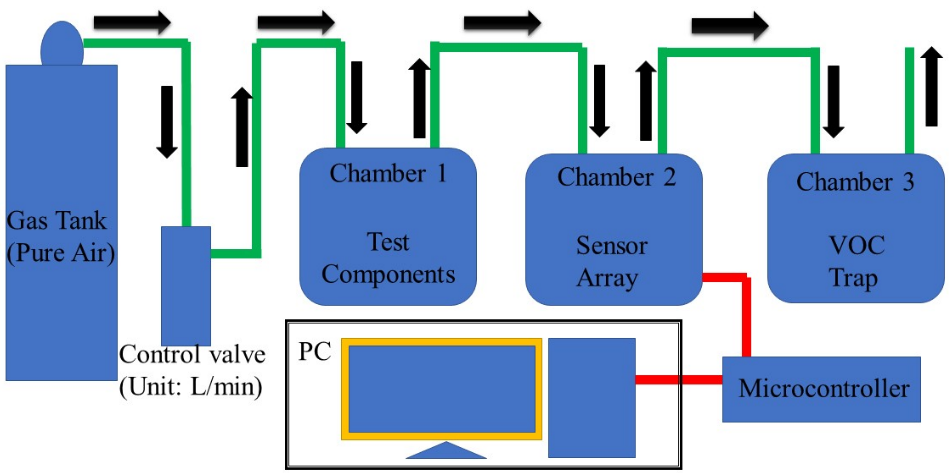


Figure 2: Test setup showing a series connection of air tank, flow control valve, air-tight glass chambers for VOC introduction and sensor array, and a VOC trap. The sensor array connects to a microcontroller which reads the sensors and feeds data to the PC during training. During testing with the trained algorithm implemented in the microcontroller, the PC was used as a serial monitor to observe and save the classification results.

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Table 1. Optimum flow rates and timing for various steps of the tests as determined through calibration tests.

Time (minutes)	Test Step	Flow Rate
0 – 5	Clear the System	1.5 L/min
5 – 6	Introduce VOC in the VOC Chamber	0 L/min
6 – 6:45	Transport Evaporated VOC from VOC Chamber to Sensor Chamber	0.5 L/min
6:45 – 12	Idle Steady State	0 L/min
12 – 15	Clear the System	1.5 L/min

2.4 Data Analysis

Test data from the sensor array placed in the Sensor Chamber was saved in a PC. For each test cycle, the measured sensor voltage increased from a baseline to a saturation level, stayed at the saturation level until the clearing began, and slowly returned to the baseline level. A sample sensor reading for one complete test cycle with 1 ppm of acetone is shown in Fig. 3. Each sensor response cycle was divided into three regions, rise: near linear voltage increase region of the curve, steady-state: saturated constant voltage region of the curve, and fall: near linear voltage decrease region of the curve. The data from ten sets of experiments with sampling every five seconds, constituted the training and testing data set for the support vector machine. As each of these tests were conducted under controlled environment, the variation in reading between tests were not different from the variation within the samples of each tests. This allowed a grouping of data to create a larger set for testing and training. Nevertheless, the data from nine tests were used for training and from one test were used for testing during the cross-validation process of determining the SMV parameters. This process was continued until all ten data sets were used for testing. This process was conducted for each of the rise, steady-state, and fall data sets, and because of higher accuracy, steady-state data was used for subsequent analyses.

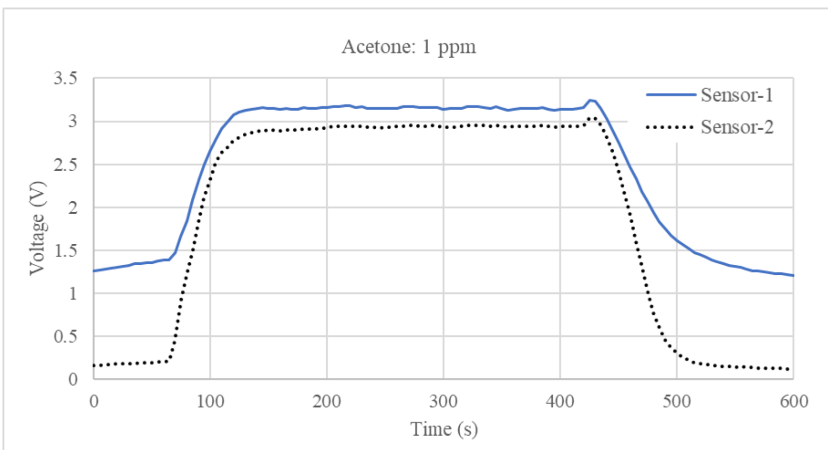

Figure 3: A sample sensor reading showing one complete test cycle with 1 ppm of acetone.

3. RESULTS AND DISCUSSION

The trained SVM was implemented in a microcontroller, which was then used for real time testing. The sensors were directly connected to the microcontroller. During the real time testing the test decision was made solely by the trained algorithm in the microcontroller. As the SVM was trained using steady-state data, the sensor response was allowed to enter steady-state by timing the reading of sensor after the introduction of the VOC signature to the sensor array. The test setup and the procedures described in the previous section was used for these tests. Once the steady-state was reached, the classification of artificial breath by the SVM was recorded every five second. Three test cycles for artificial breath corresponding to a low and high blood glucose levels were conducted. In a real time test, the trained SVM correctly identified the true class 97% of the time.

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4. SMART WRISTBAND

For implanting developed system into a wearable smart wristband, an Arduino-based Adafruit FLORA microcontroller platform was selected for its small form factor (diameter: 45 mm, thickness: 7 mm, weight: 4.4 g) and a low-power consumption [24]. Other features of the board include a GPS module, light emitting diode (LED) NeoPixels, built-in USB support for easy programming using Arduino integrated development environment (IDE), which is compatible with the developed SVM algorithm, and a 3.3 V 250 mA regulator with a protection diode. A Li-ion charger module was used to connect a 3.7 V 500 mAh rechargeable Li-ion battery. A Bluetooth module was connected to the microcontroller for communication with a smartphone app. Three MOS-based sensors were connected to the FLORA board with appropriate heater connections and voltage divider circuits. An enclosure for the wristband was created using a 3D printer. Two versions of the developed wristbands are shown in the figure below. Fig. 4(a) shows the first version of the device. 4 (b) is the side-view showing the openings for the three sensors and the sensors through the openings. Fig. 4(c) shows the second version with an opening on the top to accommodate NeoPixels display.

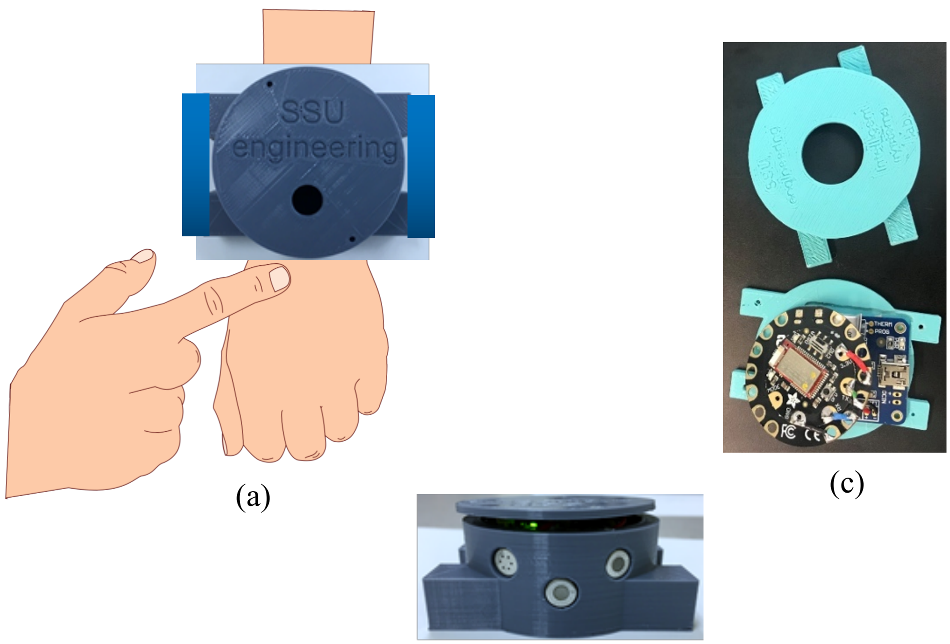

Figure 4: Two versions of wearable smart wristband prototype. (a) Initial version. (b) Side-view of the wristband in (a) showing sensors. (c) Improved version in development.

The flow chart depicting the operation of the smart wristband is shown in Fig. 5(a). To conserve power, the smart wristband stays normally in a low-power sleep mode. It wakes up every half an hour and collects and sends data to a smart phone app. As shown in the flow chart, after the system wakes up, it alerts the user by flashing red on NeoPixels display. It turns on Bluetooth and power to the sensor heaters. Next, the sensor readings are sampled and transmitted to the smartphone BlueFruit app [25]. Once the data transmission is complete, the sensors heaters are powered off, the peripherals are turned off, and end of data collection is signaled by flashing a rainbow color on the NeoPixels display. The system then goes back into the sleep mode. The BlueFruit app talks to the smart wristband via the Bluetooth module. It receives the data sent by the smart wristband and allows visualization. Screenshots of the BlueFruit app is shown in Figure 5(b). In addition, the BlueFruit app pushes the data to Adafruit cloud through MQTT protocol [26]. The Adafruit cloud logs the data, and allows visualization and retrieval of data for further analysis. The overall process is shown in the block diagram in Fig. 6.

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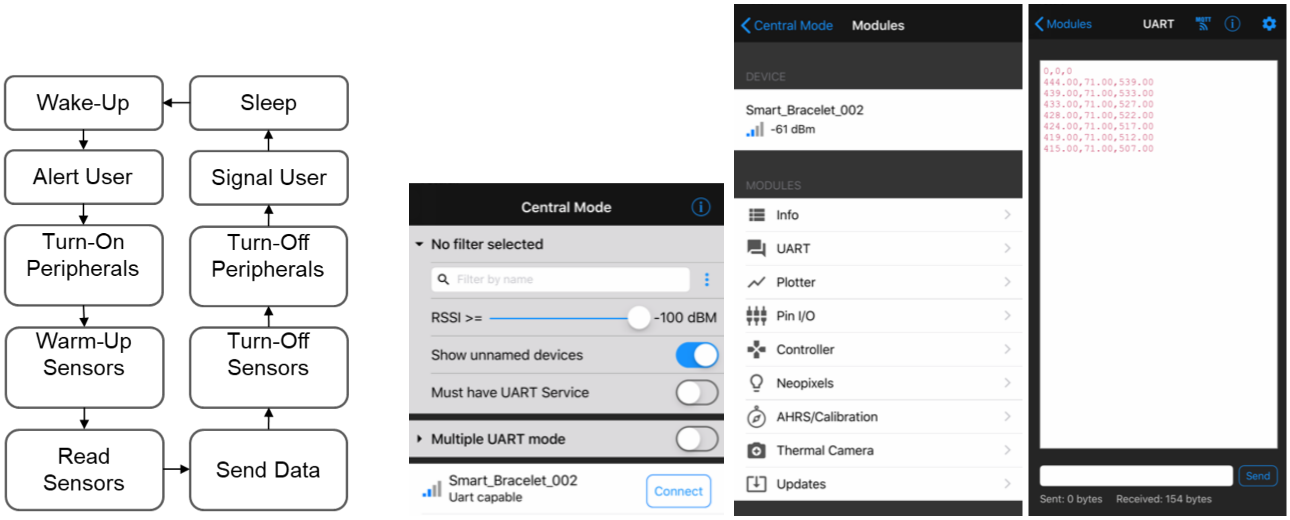

(a) (b)

Figure 5: (a) Flow chart for the smart wristband program showing major steps. (b) Screenshots showing the BlueFruit smart app on iPhone XS Max. From left to right: Main page showing smart wristband (Smart_Bracelet_002), page after the connection has been established, and receiving data from the smart wristband sensors.

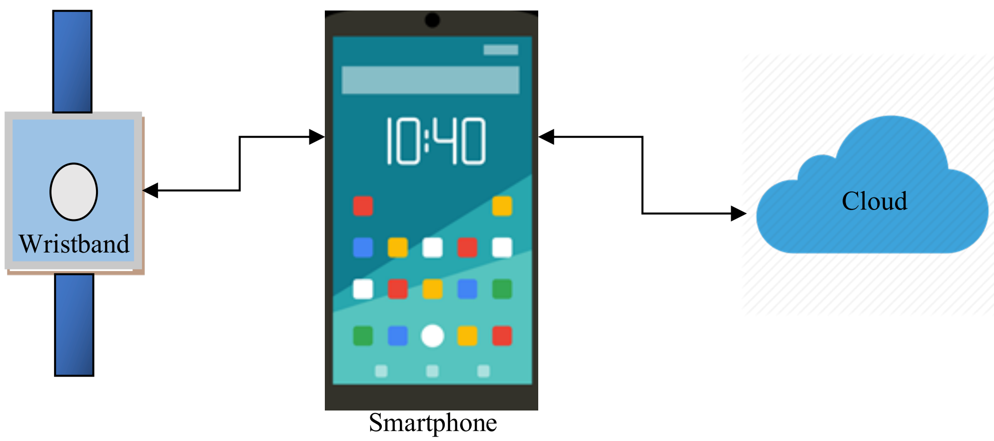

Figure 6: Block diagram showing the overall system architecture that includes the smart wristband, smartphone, and cloud.

5. CONCLUSION

A microcontroller-based solution able to classify low and high blood glucose levels using acetone and ethanol VOCs was developed and tested. Tests were conducted using humid air spiked with acetone and ethanol with concentrations consistent with those found in breath when patients have low and high blood glucose levels. An SVM algorithm trained with the experimental data was able to classify low and high blood glucose levels with 97% accuracy. A wearable smart wristband platform developed on an Arduino-based microcontroller integrates two tested sensor and one additional sensor for future use. A program was developed for the wristband to operate with a low power consumption, collect data from the sensors, communicate with a smartphone app, and eventually push the data in the cloud for further visualization and analysis.

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