Development of a PPG Sensor Array as a Wearable Device for Monitoring Cardiovascular Metrics

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Wearable devices with integrated sensors for tracking human vitals are widely used for a variety of applications, including exercise, wellness, and health monitoring. Photoplethysmography (PPG) sensors use pulse oximetry to measure pulse rate, cardiac cycle, oxygen saturation, and blood flow by passing a light beam of variable wavelength through the skin and measuring its reflection. A multi-channel PPG wearable system was developed to include multiple nodes of pulse oximeters, each capable of using different wavelengths of light. The system uses sensor fusion along with machine learning model to perform feature extraction of relevant cardiovascular metrics across multiple pulse oximeters and predict saturated oxygen (SpO₂). The developed model predicted SpO₂ with a root mean square (RMSE) of 0.07 and accuracy of 99.5%. The wearable system was applied to the plant of the foot for vascular assessment. Wearable PPG systems capable of sensor fusion demonstrates a potential capability for continuous evaluation/monitoring of wounds and diseases associated with abnormal blood flow.
DEVELOPMENT OF A PPG SENSOR ARRAY AS A WEARABLE DEVICE FOR MONITORING CARDIOVASCULAR METRICS

by

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A thesis submitted to the Graduate College in partial fulfillment of the requirements for the degree of Master of Science in Engineering Electrical and Computer Engineering Western Michigan University April 2022

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CHAPTER 1

INTRODUCTION

1.1 Background

Wearable devices such as smartwatches, goggles, and smart textiles/fabrics equipped with a multitude of sensors for tracking body temperature, pulse rate, respiration rate, blood pressure, electrocardiogram (ECG), and glucose level are being researched and developed at a very fast pace [1–4]. Advancements in electronics has created an opportunity for researchers to investigate novel approaches and develop robust, compact, reliable, and cost-effective solutions to meet the growing demand in the wearable industry [5–21]. Many healthcare professionals have been regularly tasked with the treatment of peripheral arterial disease (PAD) and peripheral neuropathy, a disorder affecting 8-12 million Americans and is most common in older patients with diabetes [22]. The PAD condition is very problematic for people with chronic wounds.

Current techniques for identifying PAD and providing localized wound assessment are limited by available devices and remain a sector with the need for novel sensing techniques. Continuous monitoring of key health indicators such as heart rate, blood flow volume, oxygen saturation, and the cardiac cycle can greatly benefit wound diagnosis and provides advanced feedback to the efficacy of various PAD or peripheral neuropathy treatments and post-operative rehabilitation. In addition, to the localized measurement and assessment of vein health and blood flow can be used as a means for determining the successful onset of anesthesia. The desire for a cost-efficient, mobile-ready biomedical sensory system that can monitor relevant
cardiovascular health factors for the treatment of abnormal blood flow diseases and wounds has led to the investigation of a wearable PPG sensor system.

Typically, a single PPG sensor is employed to monitor either one or two key health indicators. However, the measurements from a single PPG sensor is not always reliable and can lead to anomalies [23]. Additional health factors concerning the health of the individual’s veins are difficult to assess with currently available tools. To alleviate this problem and for accurate monitoring of cardiovascular metrics, an array of PPG sensors implemented as a single wearable device with machine learning capability is envisioned as a potential solution.

1.2 Organization of Thesis

This thesis is divided into four chapters. In chapter 2, the author presents a comprehensive literature review on sensors, their mechanisms, and applications. This provides an overview of sensors and their classification, mechanisms, and applications. In addition, Chapter 2 explains the aforementioned topics with an in-depth focus on optical PPG sensors. In Chapter 3, the author provides a detailed discussion on a research project that has been performed for developing the PPG array sensing system including the methodologies for accurately predicting saturated oxygen while mitigating motion artifacts. Finally, in Chapter 4, the author summarizes this work with conclusions and future work concerning this area.
CHAPTER 2

SENSORS

2.1 Introduction

In this chapter, the author presents an overview of the various types of sensors used in both research and industrial applications, as well as their mechanisms. This chapter is divided into two main sections: (2.2 Sensors) defines the sensor and its primary classifications, whereas (2.3 Optical Sensors) delves deeper into optical sensors, their function and applications. Section 2.2 contains subsection (2.2.1 Introduction to Sensors) that discusses sensors and their applications in society, subsection (2.2.2 Classification of sensors) explains several ways to classify sensors and what those classifications are. The subsections (2.3.1 Types of optical sensors) and (2.3.2 PPG Sensor Applications) in Section 2.3 Optical Sensors, respectively, cover the many types of optical sensors now in use and delve further into the applications of PPG sensors. Finally, in Section 2.4, the Sensors Chapter is summarized.

2.2 Sensors

2.2.1 Introduction to Sensors

Merriam-Webster’s dictionary defines the word ‘sensor’ as “a device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating a control)” [24]. This definition uses the standard view of the sensor from a technological device. However, there are other mechanisms that operate as sensors do in nature as well. A sensor can be fundamentally
understood as a physical material which changes some measurable property based on a characteristic that is desired to be ‘measured’ [25]. For example, a camera is a highly dense mesh of cone shaped photoreceptors that experiences electrical change (can be measured as a voltage) to represent the amount of light (characteristic to be measured) received at each receptor. There are numerous sensors that measure many properties. For example, there are resistive and capacitive based pressure sensors, and each of them have an associated sensitivity, response time, noise, and sample frequency.

Figure 2.1. Automotive sensors
Source: [https://www.bourns.com/products/automotive/automotive-sensors]

In our modern technological and scientifically advanced world, sensors are vital in every system. Figure 2.1 shows an example of different types of sensors that can be present in a single vehicle, measuring different types of properties like the fuel level, wheel angle, speed, light,
pressure etc., most of which output the sensing data as an electrical signal since the whole sensor network is an electrical system. Most industrial and commercial application sensors will use electrical output sensors since sensor data is often measured electrically, but there are other types of sensors which have no electrical basis, like pH strips or mercury thermometers [26].

2.2.2 Active and Passive Sensor Classification

It is important to define classifications for sensors because it enables scientists and engineers to understand the relationships between different groups of sensors. One kind of classification between sensors is active and passive sensors [27]. Active sensors are sensors which require an external power source or stimulus in order to function properly. An example of an active sensor is an ultra-sonic sensor which measures the distance between itself and an object by sending a sonic signal via a transmitter which then bounces back from the object and is detected by a receiver sensor, shown in Fig. 2.2(a). The transmitter is essential for the ultra-sonic sensor to function and therefore, this sensor is classified as an active sensor [28].

Figure 2.2. Passive and active sensors, (a) ultrasonic sensor, and (b) piezoelectric disc
Passive sensors are sensors which require no additional stimulus in order to operate. Some definitions describe passive sensors as sensors which do not use power, however this is not fully applicable since most passive sensors require an electrical circuit that uses power to read the data from sensor, and the selection of what part is the sensor and what other part is the measuring circuit is arbitrary. An example of a passive sensor is a piezoelectric element, or piezo discs shown in Fig. 2.2(b). The piezo disc has many applications, but it essentially generates an electric voltage when pressure is applied [29]. Common applications include vibration detection and pressure sensing. An important note to consider is that the piezoelectric effect can be used as an actuator as well, meaning the piezo element can also expand or contract via electrical stimulation, further increasing its applications. When a mechanical stress/pressure is applied, electric charge is created across the piezoelectric material proportional to the pressure applied. The piezoelectric sensor elements do not require an external voltage or current source to read the output signal, making them a passive element.

2.2.3 Transducer Based Classification

Transducers are devices that convert one type of energy into another. Sensors are a subset of transducers because they similarly convert one form of energy into another (mostly electrical since they are typically the most effective output to measure and record) [30]. Another subset of transducers are actuators, which again, would convert electrical signals to another form of energy, typically mechanical [31]. Below is a table showing various forms of electrical transducers and some example devices.
Table 2.1. Types of electrical transducers and respective devices

<table>
<thead>
<tr>
<th>Transduction</th>
<th>Devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electromechanical</td>
<td>Piezo disc, Pressure sensor</td>
</tr>
<tr>
<td>Thermoelectric</td>
<td>Thermocouple. Thermistor</td>
</tr>
<tr>
<td>Electronic</td>
<td>MOSFET, Ammeter</td>
</tr>
<tr>
<td>Electromagnetic</td>
<td>Antennae, Hall Effect Sensor</td>
</tr>
<tr>
<td>Electrochemical</td>
<td>Glucose Sensor, Humidity Sensor</td>
</tr>
<tr>
<td>Electro-optical</td>
<td>Photoresistor, Photodiode</td>
</tr>
</tbody>
</table>

For example, electromechanical sensors such as pressure sensors measure mechanical stimulation and convert it into an electrical signal. There are three main types of pressure sensor mechanisms including resistive, capacitive, and piezoelectric. Resistive based pressure sensors (Fig.2.3) can use polymer thick films that exhibit a decrease in resistance with increase in force applied to the surface of the sensor. Such sensor can be integrated into a Wheatstone bridge where the voltage difference between the two nodes is proportional to the resistance of the sensor, which in turn is proportional to the pressure being applied [32]. This circuit can be used with other types of resistive mechanical sensors like strain gauges where their resistance changes based on the curvature of the film. Next, capacitive based pressure sensors consist of a set of plates with a dielectric material in between that can decrease the distance between the plates in proportion to the applied pressure. The area of the plates, thickness of dielectric and the young’s modulus of the dielectric, or malleability, play an important role in the sensitivity and range of the sensor[33]. A capacitance measurement circuit consisting of capacitance-to-voltage
converter and an operational amplifier can be used to energize the capacitor and read the output of sensor. Using a microcontroller, it is also possible to energize the capacitor and time the rate at which the voltage increases to represent the capacitance. Finally, piezoelectric based pressure sensors utilize the piezoelectric effect of materials like quartz. As mentioned earlier, piezoelectric materials generate a voltage when pressure is applied. So, capturing the signal is only a matter of measuring the output voltage. One important characteristic is that the piezoelectric charge generated by the applied pressure dissipates quickly, so they are not optimal for absolute pressure measurements. Their applications are better suited for measuring phenomena of sinusoidal nature like vibrations, or acoustics[34-35].

![Figure 2.3. Resistive based pressure sensor](image)

Another example includes thermoelectric sensors that measure temperature or a relative temperature change. The two main types of thermoelectric sensors are the thermistor and the thermocouple. There are negative and positive coefficient thermistors (NTC and PTC). NTC thermistors are made using a semiconducting material such as sintered metal oxides [36]. As temperature increases, the semiconductor increases the number of active charge carriers that are promoted into the conduction band, and thus decrease their resistance as temperature rises.
A significant disadvantage of NTC thermistors is that they typically have a low temperature accuracy and poor interchangeability [37]. PTC thermistors are made from doped polycrystalline ceramic [38]. Below the curie point temperature, it acts as a small NTC, however over the curie point temperature, the dielectric constant drops sufficiently to allow the formation of potential barriers at the grain boundaries, and thus the resistance sharply increases with increasing temperature. Thermocouples (Fig. 2.4) operate under the Seebeck effect, where two dissimilar electrical conductors forming an electrical junction generates voltage under a temperature difference [39]. This voltage represents the temperature and thermocouples are considered as passive devices. However, they are not as accurate as their thermistor counterparts, having difficulty achieving a resolution of less than one degree Celsius.

![Thermocouple functionality with two electrical conductors (Wire type A and B)](image)

Electronic transducers convert one form of electrical input into a different type of electrical output. Not every transducer is considered as a sensor, for example a transformer is an electric transducer which converts an AC voltage into an AC voltage with different amplitude (higher or lower amplitude when compared to input signal), but it is not considered a sensor. Electronic transducer sensors include voltmeters, ammeters, and ohmmeters, which are often
found in digital multimeters. Many of the other types of sensors discussed will require an intermediary electric sensor to interpret electric output, like voltage. A more fundamental device that is worth mentioning is the metal-oxide-semiconductor field-effect transistor (MOSFET) and other similar type of transistors. They are insulated gate field-effect transistors fabricated by the controlled oxidation of a semiconductor, typically silicon [40] as shown in Fig. 2.5. The input of the device is the voltage of the gate terminal with respect to the drain terminal. However, the output is a change in conductance between the source and drain terminals with a given voltage between them. It is perhaps the single most important electronic sensor, the building block of digital electronics, and vital in the construction of instrumentation circuits.

Electromagnetic sensors measure the surrounding electromagnetic fields. Hall effect sensors detect the presence of a magnetic field and output a corresponding voltage using the Hall effect [41]. The sensor works by running an electrical current across an electrical conductor and when a magnetic field is applied, a voltage is produced transverse to the current direction as shown in Fig. 2.6. A popular industrial application for hall effect sensors is position sensing for
brushless DC motors. Commercially they are often used for detecting when a smartphone’s cover is closed. Conversely, antennas are employed as the main sensors for detecting signals in the electromagnetic spectrum. In antenna design, it is important not to perturb the electromagnetic field, to prevent coupling and reflection leading to inaccurate results [42]. Antennas are widely used in wireless telecommunications, from low frequency radio to high frequency Bluetooth or Wi-Fi [43-45]. They also have non communication applications. For example, metal detectors use antennas to induce electric current in metals inside the magnetic field, which then can be detected [46].

![Figure 2.6. Hall effect diagram](image)

Electrochemical sensors are used to detect the presence of a chemical substance. The detection of certain chemicals is essential in many areas from industrial to commercial applications. Some examples include humidity sensors integrated into air conditioning systems [47, 48], blood glucose testers that are widely used by people with diabetes [49, 50], carbon monoxide sensors that have been standardized in every home, etc. Every electrochemical sensor
uses either capacitive or resistive based sensing and needs to be calibrated with respect to the chemical analyte it is made for. In biosensing applications, electrochemical sensors are typically implemented in either two or three electrode systems. In a two-electrode system, a working electrode acts as a reference electrode while the counter electrode is the measuring electrode that outputs the voltage. In a three-electrode system, a third reference electrode is introduced to act as the voltage reference for the working electrode which measures the voltage, and the counter electrode induces a current into the system (Fig. 2.7). The three-electrode system provides greater accuracy when compared to the two-electrode system [51].
## 2.3 Optical Sensors

### 2.3.1 Types of Optical Sensors

Electro-optical sensors, also called photoelectric sensors, convert light into an electronic signal. There are two main types of photoelectronic sensors: the photoresistor and photodiode. The photoresistor, also known as photocell, is a resistive element that decreases its resistance with respect to the luminosity \([52]\), shown in Fig. 2.8(a). The most common type of photoresistor is the cadmium sulfide cells \([53]\). When photons hit the photosensitive material, bound electrons are given enough energy to jump into the conduction band. The resulting free electrons lower the resistivity of the material. The latency in the resistive response, which takes roughly 10 milliseconds when switching from dark to light, while taking about a second when going from light to dark, is one of photoresistors' shortcomings \([54]\). This constraint prevents them from detecting high frequencies of light change; yet, for applications such as sensing nightfall for outdoor or interior lights, they are adequate and cost effective.

Another important type of optical sensor is the photodiode as shown in Fig. 2.8(b). The photodiode is a semiconductor p-n junction diode that creates an electrical current proportional to the intensity to light exposure. This is possible due to the photovoltaic effect \([55]\), where the light absorption causes an excitation of an electron to a higher energy state creating an electron-hole pair. Due to the electric field of the depletion region, the hole moves towards the anode and the electrons toward the cathode, creating a photocurrent \([56]\). This is the case if there is a short between the diodes, or if there is a low impedance load, otherwise if the impedance is high enough, the charges gather creating a voltage. Solar cells, which are photodiodes, operate on
this principle. It is worth noting that photodiodes can also work in reverse, with electrons recombining with electron holes and releasing energy in the form of photons when a forward bias current is applied across the diode. Light-emitting diodes (LEDs) work in this manner [57].

![Figure 2.8. Photosensors, (a) photoresistor, (b) photodiode](image)

Optical sensors have a wide range of applications. Perhaps the most popular application is the camera. Cameras employ a digital camera sensor (DCS) that has a dense matrix of devices called photosites that effectively operate as photodiodes [58]. When photons strike these devices, they generate a charge, and the camera processor reads the amount of charge in each photosite to calculate the brightness of each pixel. While DSCs are one of today's most advanced microelectromechanical systems (MEMS) based devices [59], photodiodes are also used in a variety of other applications. Garage door openers employ a laser-based device that sends light into a photodiode to ensure that there isn't anything in the way when the door closes.

### 2.3.2 PPG Sensor

Photodiodes are also widely used in the medical field to monitor health parameters such as heart rate and oxygen saturations. These sensor packages are known as photoplethysmography (PPG) sensors. They effectively combine one or more LEDs with a
photoreceiver array. The LEDs act as light transmitters, transmitting light into the skin, and the photoreceiver receives a portion of the light sent, as shown in Fig. 2.9. The PPG created can provide information about the patient's health by continuously measuring the absorbed light from the photoreceiver [60]. PPG's use is just not limited to medical applications. Because the amount of transmitted light that is reflected into the photoreceiver is related to the distance between the PPG and the object, PPGs can be utilized as proximity sensors. In addition, PPG has smoke detection applications since light is absorbed by smoke particles in a smokey atmosphere, reducing the amount of light received by the PPG [61].

![PPG sensor principle](image)

**Figure 2.9. PPG sensor principle**

Clinically, PPG is a non-invasive method that can continuously sense changes in blood flow volumes, respiration, blood oxygen saturation, and can monitor blood pressure as well as the heart rate of a subject [62]. PPG sensors can be implemented in a wearable device due to their small size, simple operation, portability, and relatively low cost. There are two different
implementations of PPG: reflectance type and transmittance type. The reflectance type has both the LED transmitters and photoreceptor on the same side, meaning the received light comes from the reflection of vascular objects inside the skin. Transmittance type PPG have the transmitter and receiver in opposite ends. The transmittance PPG has the disadvantage of being confined to extremities like the finger, toe, or earlobe since its accuracy is dependent on vasoconstriction, correct probe placement, and motion artifacts, whereas the reflectance type PPG can be used in more diverse locations like the wrist, chest, forehead, overcoming the drawbacks of transmittance PPGs [63].

2.3.3 Heart Rate and Saturated Oxygen Measurement

A PPG signal consists of an pulsative component (AC) and a nonpulsative component (DC), represented in Figure 2.10. The AC is synchronized with the heartbeat, while the DC relates to the light absorption of arterial and venous blood, in addition to tissue, bone and others [64].

![Figure 2.10. PPG AC and DC signal components](image-url)
From this phenomena, PPG was suggested as a technique to measure blood volume changes from the area irradiated with light [65]. This can be explained by the Beer-Lambert’s law that defines the attenuation of light related to the material properties from which it’s traveling [66]. This principle is described in Eq. (1).

\[
PPG(t) = I_0 \times e^{-(\varepsilon \times c \times d)} + I_{tis} \tag{1}
\]

\[
r(t) = \frac{1}{-2 \times \varepsilon \times c} \ln \left( \frac{PPG(t)-I_{tis}}{I_0} \right) \tag{2}
\]

where \( I_0 \) represents the light intensity, \( \varepsilon \) is the absorption coefficient, \( c \) is the Mohr concentration of the blood, \( d \) is the path length of light traveling through blood vessels, and \( I_{tis} \) is the stationary component from nonpulsative sources. This formula can be used to analytically derive the vessel radius \( r(t) \), shown in Eq. (2), in addition to estimating SpO\(_2\) via machine learning methods [67]. Eq. (1) and Eq. (2) describe the instantaneous value of blood flow, however it’s parameters are often difficult to control, in addition their accuracy is often not required, whereas the average blood flow volume is more applicable and desirable in clinical applications.

A more practical way of measuring SpO\(_2\) is through the method of pulse oximetry, invented by Dr. Takuo Aoyagi in 1974 [68]. Pulse oximetry operates on measuring the light absorption of multiple wavelengths for both hemoglobin (or oxyhemoglobin) and deoxyhemoglobin [69]. Hemoglobin is a protein in red blood cells that carry oxygen molecules to transport to organs and tissues. Once the oxygen molecule is released it is known as deoxyhemoglobin [70]. These two forms of hemoglobin actually have different spectrograms, meaning they absorb different amount of light from light of different wavelengths. The
spectrogram of hemoglobin and deoxyhemoglobin is shown on figure 2.11. Red light, of around 700nm wavelength, reflects substantially from hemoglobin, while deoxyhemoglobin absorbs this light. The opposite effect is observed for infrared light (IR), of around 900nm wavelength. Because of red and IR light’s sensitivity to hemoglobin, they are used to compute an approximation of SpO₂.

![Figure 2.11. Optical absorption of hemoglobin](image)

For each LED, the ratio between the AC and DC component is known as the perfusion index (PI). This works as an indicator of the pulse strength of the LED light [71]. The ratio between the PIs of the red and IR LEDs is referred to as the IR LED R ratio, as defined in Eq. (3), and similarly, the ratio between the PI’s of the red and green LEDs is referred to as the green LED R ratio. This R ratio is used in the standard model of SpO₂ computation, defined as Eq. (4). However, accurate SpO₂ calculations will be based on empirical calibration of the IR ratio for the specific device.
$$R = \frac{AC\ of\ Red}{DC\ of\ Red} \frac{AC\ of\ IR}{DC\ of\ IR}$$  \hspace{1cm} (3)

$$SpO_2 = 110 - 25 \times R$$  \hspace{1cm} (4)

Saturated oxygen (SpO₂) is an important component of hemoglobin, the major protein in red blood cells that carry oxygen throughout the body [72]. SpO₂ is important for carrying out biological processes, such as breath holding, heart rate stability, organ function, and maintaining the body’s pH levels. Low levels of SpO₂ can result in hypoxia. Insufficient intake of oxygen can be fatal and can lead to damage of the brain, lungs, and liver. [73]. It is often desirable to monitor SpO₂ in order to determine the state of a subject’s health during any physical activities. The opposite effect occurs with the IR light. Some PPG sensors use a green LED instead of IR, since it has similar characteristics to IR.

2.4 Summary

In this chapter, the author introduced the concept of the sensor and explored the various classification of sensors. A detailed overview of the types of sensors, their mechanisms, and applications as well as optical sensors and the optical sensor functionality was included. Then, the author introduced the PPG sensor and provided an overview of the device, working mechanism, and applications, specifically clinical application for monitoring health metrics.
3.1 Introduction

In this thesis, a printed circuit board (PCB) based PPG sensory array device with sensor fusion capabilities has been developed that can not only detect the key health factors by measuring the physiological signals but also calculate the localization treatment effectiveness based on the sensor fusion results. The PPG sensor array device was integrated with a temperature sensor, accelerometer, and optical filters to mitigate the effect of motion artifacts and ambient light. The initial version of the PCB system, developed to test functionality, will be eventually transitioned as a complete wearable device using polyimide based flexible substrate. With flexibility, the system can be placed directly on the subject and conform to the body contour.

3.2 Experimental

3.2.1 Machine Learning Model for SpO₂

Figure 2.1 shows a 10 second sample of the PPG signal for IR, red and green LEDs with their DC component removed, and 100 unit offset so the signals can be compared side by side. Source code is provided in the Appendix. The IR LED signal has the most distinguishable peak, so it is the signal chosen for peak detection to calculate the heartbeat. The IR, red and green signal has an average integer amplitude of 758, 242 and 24, respectively, given by the analog to digital convertor (ADC) of the PPG chip. Even though the green signal has a relatively smaller amplitude,
it is sensitive to changes in SpO$_2$. The sensor fusion process takes advantage of the green LED’s response to SpO$_2$ in addition to that of IR. Later, the same peak locations were used to analyze and compute the specific SpO$_2$ value for each pulse. Buffering these values and computing the mean accurately represents the overall SpO$_2$ present in the body.

![PPG Signal](image)

**Figure 3.1.** PPG signal from IR and red LED

To accurately predict SpO$_2$, a real-time machine learning model for time-series data is an excellent solution for continuous low latency predictions. The classification system architecture is based on the advanced deep learning technology of the long short-term memory (LSTM) architecture. The LSTM is a recurrent neural network that can remember long term dependencies from its unique architecture [74]. An LSTM element is composed of four gates and two cell states that modify, modulate, and update information across the cell state traversal. The input gate ($i$) determines whether to write information into the cell. The forget gate ($f$) determines whether to
erase information in the cell. The input modulation gate \((g)\) determines how much to write into the cell. Finally, the output gate \((o)\) determines how much information to reveal in the output of the cell. The hidden state \((h_t)\) and cell state \((c_t)\) carry information and context as the LSTM continues through a sequence. Their previous iterations are used to calculate the gates based on the current state.

To compute the gate values, a weight matrix \((W)\), composed of \([w_i, w_f, w_o, w_g]\), must be multiplied by the vertical concatenation of the previous hidden state \((h_{t-1})\) and the current input \((x_t)\), then sigmoid and tanh functions are applied to the appropriate portions of the result to form the gates, as shown in Eq. (5), Eq. (6), Eq. (7), and Eq. (8). The functions for the hidden state and cell state are shown in Eq. (9) and Eq. (10). Given an initial \(h_{t-1}, c_{t-1},\) and \(x_t\), the output \(h_t\) can be computed, which is the output of the network. The cell state variables are recursive since for every time-step, the computed variables are fed back into the cell. To train the neural network, a stochastic optimization algorithm called Adam is used. Adam has demonstrated to be computationally efficient solution to many gradient-based optimization problems [75].

\[
i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (5) \\
f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (6) \\
o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (7) \\
g_t = \text{tanh}(w_g[h_{t-1}, x_t] + b_g) \quad (8) \\
\]

\[
c_t = f*c_{t-1} + i*g \quad (9) \\
h_t = o*tanh(c_t) \quad (10) \\
\]

In this work an input dataset at time \(t\) represented by \(X_t\) \((X_t = [IR_R, Green_R, IR_AC, Green_AC, HR])\), where \(IR_R\) and \(IR_AC\) is the ratio and AC for the IR LED, \(Green_R\) and \(Green_AC\) is the ratio and AC for the green LED, and \(HR\) is the heart rate, features all measured
at time $t$). These features have shown to be correlated to $\text{SpO}_{2}$, especially the ratio value. After training, the LSTM takes $Xt$ as the input, and returns a prediction $Ot$, which is in turn a prediction for $Dt$, the actual $\text{SpO}_{2}$.

### 3.2.2 Multi-Channel Sensor Fusion

Current PPG integrated circuits typically use red and IR LEDs for relevant cardiovascular feature extraction. However, indices obtained from individual PPG sensors at specific extremity points can yield different insights into an individual’s health. A channel represents a single source of light, and its corresponding value is read by a PPG IC. The approach presented is to use multiple PPG sensors and distribute them across a selected extremity to perform transient and value-based analysis between channels. The PI and its first derivative at each sensor location can be calculated by the local microcontroller or externally by the client application. Based on the PI and its first derivative, localized real-time monitoring of blood flow can be estimated at a specified extremity.

A challenge associated with PPG sensing is to achieve a high signal to noise ratio (SNR). The author’s approach focused on sensor fusion, integrating multiple sensors of different light wavelengths to improve the SNR across the system. Specifically, each PPG sensor contains its own temperature sensor for temperature compensation. Additionally, the microcontroller circuitry contains an additional external 16-bit resolution temperature sensor. Lastly, the microcontroller circuitry contains an external MEMS gyroscope and accelerometer that assists with motion artifact filtering. The specific location of the PPG sensors also plays an important role in the quality of the signal obtained. Typically, PPG sensors are placed on the hand’s finger.
to obtain good results. However, in this work, the PPG system was designed for the foot (to accurately measure the SpO\textsubscript{2} and other cardiovascular metrics as close to the wound area in the foot region) and can be redesigned to any other specific place on the body [76].

3.2.3 System Architecture

Figure 3.2 shows a block diagram of the designed foot mounted PPG sensor system. The system architecture was designed to support the multi-channel PPG system and consisted of a microcontroller I2C master, multiple I2C slave sensor devices, and PPG sensor array. The microcontroller I2C master is responsible for wireless communication to the wireless receiving client device and polling of the I2C slave sensor devices that perform sensor measurements. The client device receives transmitted data and can be used for feature extraction or further data pipelining, as shown in Fig. 3.3. A more detailed data flow-chart for the microcontroller system is shown in Fig. 3.4.

![Figure 3.2. PPG sensing system block diagram](image)
3.2.4 System Prototypes

Multiple prototype PCBs were fabricated to test the features of the ESP32 microcontroller as shown in Fig. 3.5. A foot shaped prototype, shown in Fig. 3.5(a), had PPG sensors implemented on the heel, the metatarsal phalangeal joint, and the hallux. The dimensions of the PCB board are 198 mm × 93 mm ×1.6 mm, weighs 43.6 g and can be customized to fit any foot size and shape. The microcontroller section of the board is a 2-layer PCB with two ground planes and two signal
layers to simplify connections. The power management has been split between three voltages: 1.8 V, 3.3 V, and 5 V. The PPG sensor logic is driven by 1.8 V; the multiplexer, accelerometer, and ESP32 are driven by 3.3 V, and 5 V is required for powering the PPG sensor LEDs. This is especially important for the green LED since they require relatively higher forward voltage. The PPG system was powered by two 3.7 V batteries that were connected in series and the microcontroller section which consists of ESP32-PICO, UART, and power management. The microcontroller section consumes an average power of 198 mW whereas each PPG sensor modules consumes an additional 20 mW. A different version of the PCB is split between the main microcontroller part and the PPG sensor modules, shown in Fig. 3.5(b). This design enables general functionality as the PPG sensors were not in a fixed location but can be placed at any desired location. In addition, if a sensor module is malfunctioning, it can be replaced seamlessly without the need of a new board.
3.3 Results and Discussion

3.3.1 PPG Response to SpO₂

To test the effectiveness of the PPG sensors and its capability to detect SpO₂, the R ratio response computed from the IR PI and the green PI was measured throughout a series of breathing exercises meant to increase and decrease the SpO₂ in the subject’s body. Figure 3.6 shows the results of the R response of the IR LED and the green LED, respectively for a duration of 130 seconds. For the first 50 seconds, the subject was breathing at a natural rate, for the next 50 seconds, the subject was breathing deeply, and the for last 30 seconds the subject was holding the breath. The results demonstrate the inverse proportionality between R and SpO₂ for both green and IR LEDs. The increase of R during the first phase of the test can be attributed to the subject’s own breathing patterns. Further measurement after the third phase should indicate
even higher values than shown. Holding the breath results in more oxygen deprivation when compared to one’s own natural breathing pattern.

Figure 3.6. (a) IR LED response and (b) green LED response
The IR LED shows a relatively linear response to the changes of breathing patterns. However, a delay in the LED response can be observed which is evident from the R-ratio peaks being delayed by approximately 20 seconds for every change of breathing exercise. This delay can be attributed to the time required for the spreading of oxygen throughout the body (in this case, from heart to foot) and also depends on the sensitivity of the device to detect such changes.

The green LED shows a relatively faster response to breathing changes when compared to IR LED, however it displays a large amount of noise, which increases the overall error in the acquired measurements. This is where sensor fusion can help combine sets of information into accurate and useful data.

3.3.2 Blood Flow Detection

Blood flow is an important measurement in determining health, but it is also difficult to be accurately measured. PPG sensors have been used to estimate blood flow [77]. Studies exploring the effects of heat on blood vessel dilation have found PPG sensors to be a more accessible and less invasive way to measure blood flow when compared to other methods, like laser-doppler flowmeters [78]. Neural networks have shown to be an effective way to estimate blood flow based on PPG data, especially if information about SpO₂ and blood pressure is available [79]. The blood flow is directly proportional to the AC component of the PPG signal. The changes in the blood flow from heartbeats will induce changes in light absorption the blood, manifesting as the AC component of the PPG signal. There are other sophisticated methods of measuring the blood flow more accurately, but for the purposes of merely identifying a change in blood flow, analyzing the AC component of the PPG signal is adequate.
The effectiveness of the proposed model was validated using the results from an experiment using two PPG sensors. One PPG was placed at the ball of the foot, and another at the toe, shown in Figure 3.7. A wire was wrapped in between these locations such that the user can pull and restrict blood flow towards the toe, indicated by the red dotted line. The user started in a resting position, then pulled the wire and finally released the wire, each step following 30 seconds. The green AC was too small to be analyzed and thus was omitted.
Figure 3.8. (a) AC of PPG located at the ball of the foot; (b) AC of PPG located at the ball of the toe
Figure 3.8 (a) shows the AC component of the PPG signal at the ball of the foot. Since, the wire was located below the ball of the foot, no distinguishable changes were observed in the AC component between the resting and flow reduction periods. Figure 3.8 (b) shows the AC component of the PPG in the toe. It shows a distinguishable decrease in AC during the flow reduction period. The average DC component during no blood flow reduction, was 172, and during blood flow reduction was 155. The IR LED showed an indistinguishable amount of change. This shows that changes in blood flow can be identifiable by analyzing the AC component of the red PPG signal located in the concerned area.

3.3.3 SpO₂ Prediction using Machine Learning Model

To predict SpO₂ using machine learning model, the MAX30105 chip was attached to the left index finger of the subject and a commercial pulse oximeter (CHOICEMMED Sky Blue, China) was attached to the right index finger to measure the heart rate and SpO₂. The subject was made to perform multiple breathing cycles over a period of 800 seconds involving deep breathing and holding breath in order to induce changes in SpO₂ and monitored using the attached PPG sensors. During the experiment, the data measured by the chip was processed using the machine learning model to compute the predicted SpO₂.
Figure 3.9. (a) IR ration breathing test and (b) green ration breathing test
In Fig. 3.9, the measured R ratio of the IR and green LEDs of the PPG sensors passed through a lowpass filter is shown. The green and red are a representation of the subject’s deep breathing holding breath patterns, respectively. The graph shows the R ratio responding to the changes in breathing. The IR ratio data is less noisy than the green ratio data. However, the green ratio responds more significantly to the peaks at the start of the test than the IR ratio data. Using sensor fusion, the features of both LEDs was combined to construct a relatively accurate model of SpO₂.

Figure 3.10. Results from predicted SpO₂
Figure 3.10 shows the measured SpO$_2$ against the predicted SpO$_2$. The LSTM trained the first 700 seconds of the experiment and predicted the last 100 seconds of the SpO$_2$, the data which it had not seen, with an RMSE of 0.07 and accuracy of 99.5%. Using all the information from the available LEDs, photodiode and their corresponding features, the LSTM was able to accurately predict the SpO$_2$ of the subject.

### 3.3.4 Motion Artifact Removal

The PPG system can be an extremely useful tool; however, its signal is easily susceptible to motion artifacts. Researchers have aimed to create motion artifact cancelling algorithms for PPG applications [80, 81]. Adaptive filters, that are widely used as motion artifact cancelling algorithms, can constantly update their parameters adaptively based on a reference signal correlated with the noise. This makes them a popular construct for real-time applications.

Figure 3.10 shows a block diagram of the adaptive filter. It contains an accelerometer, to measure the motion artifacts ($X(s)$) that the subject experiences. Using Fast Fourier Transform (FFT), the accelerometer data transformed into the frequency domain $f(X(s))$ where the frequency of the motion was identified. Then, using stop-by filters, the component of the noisy PPG signal ($S(n) + M(n)$) with the motion artifact frequency was removed, $S(n) + M(n) - f(X(s))$ and mathematically calculated using Eq. (7).

$$M(n) = f(X(n)) \quad (7)$$

Where, the motion $M(n)$ is identified with the frequency spectrum of the accelerometer data $X(s)$.  

35
Figure 3.12 shows the results of an experiment where the subject’s hand was strapped with the PPG system (PPG sensor attached to the index finger). The arm was moved up and down, resulting in a constant movement at ≈2.4 Hz. The subject stayed idle for the first 12 seconds and then began moving the arm. Figure 3.13 (a) shows the FFT graph of the accelerometer data, indicating the motion’s frequency peaks at around 2.4 Hz and the result of the stop-by filter in which the frequency around the motion artifact is removed. The signal is filtered across a 1.5 Hz band-gap and finally, in Fig. 3.13 (b) the output of the corrected PPG signal is shown against the original noisy PPG signal. A high-pass filter can also be added to flatten the signal and improve AC measuring algorithm.
Figure 3.12. Acceleration data of the subject in idle and motion conditions.
Figure 3.13. (a) Signal processing of original PPG, filtered PPG, and acceleration data using FFT, (b) motion artifact-filtered PPG signal against the original.
CHAPTER 4

CONCLUSION AND FUTURE WORK

4.1 Conclusion

A wearable multi-channel PPG system to monitor SpO$_2$ and other cardiovascular metrics (blood flow and heart rate) was developed. The system includes multiple nodes of pulse oximeters to acquire PPG signals. The R ratio was increased by 0.3 for both the green and red LEDs when the breath was held for over 30 seconds unlike the R ratio of IR and Red LEDs, which was found to be unstable. When reducing blood flow in the foot, the DC component of the Red LED decreased by 9.8%, whereas the IR LED had no distinguishable effect. Integration of multiple sensor nodes enabled the implementation of sensor fusion algorithms to improve sensor accuracy. Sensor fusion combines features of various R ratio’s, AC component and heart rate to increase data quality and accuracy. The LSTM network predicted SpO$_2$ with 99.5% accuracy from the validation data. The wearable system was designed for vascular assessment from the foot, which increases ease of wear and decreases device invasion. The PPG system capable of sensor fusion demonstrates potential capability for continuous evaluation/monitoring of wounds and diseases associated with abnormal blood flow.

4.2 Future Work

Future work is focused on addressing the rigidity of the PCB and providing conformability for positioning the sensors on a subject’s foot contour by transitioning the current prototype to a polyimide based flexible substrate, similar to previous works [82–84]. In addition, as part of the packaging process, the circuit along with its electronic components (except the PPG sensors) will
be coated with an electrical insulating varnish and covered with an ultra-thin, soft memory foam pad to avoid any discomfort and direct contact with the foot. Also, due to the recent significant progresses that have been made in the flexible and stretchable hybrid electronics field, the rigid PCB/polyimide based flexible PPG system can also be ported to a complete robust, flexible, and stretchable PPG system by using elastomers such as polydimethylsiloxane (PDMS) with microfluidic channels as substrates and liquid metals such as gallium as conductive traces similar to multiple works summarized by Yang et al. and other sensor applications [85–264].
REFERENCES


Texas Instruments, “How to design peripheral oxygen saturation (SpO₂) and optical heart rate monitoring (OHRM) Systems using the AFE4403,” Application Report, 2015


Processing (ICCSP), Melmaruvathur, pp. 1812-1816, DOI: 10.1109/ICCSP.2016.7754480, 2016.


[79] P. Chao, P. Chiang, “Theoretical development with proper approximation and the corresponding clinical experiments for ppg sensor monitoring blood flow volume of


Code for Microcontroller reading PPG data

// I2Cdev and MPU6050 must be installed as libraries, or else the .cpp/.h files

// for both classes must be in the include path of your project

#include "I2Cdev.h"
#include "MPU6050.h"
#include "MAX30105.h"

#define TCAADDR 0x70

unsigned long timLED = 1;
unsigned long timStart = 1;
unsigned long timPPG = 0;

boolean debug = false;

boolean LEDflag = true;

boolean crash = false;

byte startup = 1;

byte ledBrightness = 100; //Options: 0=Off to 255=50mA

byte sampleAverage = 4; //Options: 1, 2, 4, 8, 16, 32

byte ledMode = 3; //Options: 1 = Red only, 2 = Red + IR, 3 = Red + IR + Green

int sampleRate = 400; //Options: 50, 100, 200, 400, 800, 1000, 1600, 3200

double serialRate = sampleRate / sampleAverage;

int sensorFail = 0;
int pulseWidth = 411; //Options: 69, 118, 215, 411
int adcRange = 8192; //Options: 2048, 4096, 8192, 16384

struct ppg {
    MAX30105 obj;
    uint32_t IRValue;
    uint32_t RedValue;
    uint32_t GreenValue;
    uint32_t temp;
    boolean aval;
};

ppg sen[3];

// Arduino Wire library is required if I2Cdev I2CDEV_ARDUINO_WIRE implementation
// is used in I2Cdev.h
#if I2CDEV_IMPLEMENTATION == I2CDEV_ARDUINO_WIRE
#include "Wire.h"
#endif

MPU6050 accelgyro;

//MPU6050 accelgyro(0x69); // <-- use for AD0 high
int16_t ax, ay, az;

int16_t gx, gy, gz;

#define OUTPUT_READABLE_ACCELGYRO //Slow tab separated UART

//#define OUTPUT_BINARY_ACCELGYRO //Fast, hard to parse

#define LED_PIN 13

TaskHandle_t Task1;

void tcaselect(uint8_t i) {
  if (i > 7) return;

  Wire.beginTransmission(TCAADDR);
  Wire.write(1 << i);
  Wire.endTransmission();
}

MAX30105 ppgSetup(int chn) {
  tcaselect(chn);
  delay(10);
  MAX30105 sensor;
  // Initialize sensor 1
  if (sensor.begin() == false) {
/ **Serial.print("Sensor ");**

**Serial.print(chn);**

**Serial.println(" was not found.");**

sen[chn].aval = 0;

    return sensor;

} else {
    sen[chn].aval = 1;
}

sensor.setup(ledBrightness, sampleAverage, ledMode, sampleRate, pulseWidth, adcRange);

//Configure sensor with these settings

Serial.print("Successful setup of Sensor ");

Serial.println(chn);

delay(10);

return sensor;

}

void setup() {

    Serial.begin(38400);

    pinMode(13, OUTPUT);

    digitalWrite(13, HIGH);
// join I2C bus (I2Cdev library doesn't do this automatically)

#if I2CDEV_IMPLEMENTATION == I2CDEV_ARDUINO_WIRE
  Wire.begin();
#elif I2CDEV_IMPLEMENTATION == I2CDEV_BUILTIN_FASTWIRE
  Fastwire::setup(400, true);
#endif

xTaskCreatePinnedToCore(
  Task1code,   /* Task function. */
  "Task1",     /* name of task. */
  10000,       /* Stack size of task */
  NULL,        /* parameter of the task */
  1,           /* priority of the task */
  &Task1,      /* Task handle to keep track of created task */
  0);          /* pin task to core 0 */

delay(500);

tcaselect(7);

// initialize device

Serial.println("Initializing I2C devices...");

accelgyro.initialize();
// verify connection

Serial.println("Testing device connections...";

Serial.println(accelgyro.testConnection() ? "MPU6050 connection successful" : "MPU6050 connection failed");

// use the code below to change accel/gyro offset values

Serial.println("Updating internal sensor offsets...");

// accelgyro.setXAccelOffset(0);

// accelgyro.setYAccelOffset(0);

// accelgyro.setZAccelOffset(0);

Serial.println("Setting up sen0");

sen[0].obj = ppgSetup(0);

sen[1].obj = ppgSetup(1);

sen[2].obj = ppgSetup(2);

if (debug) { // Edit ppg enabling

    sen[0].aval = 1;

    sen[1].aval = 1;

    sen[2].aval = 1;
startup = 0;
Serial.println("Set up is done!");

void Task1code( void * pvParameters ) {
    Serial.print("Task1 running on core ");
    Serial.println(xPortGetCoreID());

    for (;;) {

        delay(10);

        if (millis() - timLED > 500) {
            timLED = millis();
            if (LEDflag) {
                digitalWrite(13, HIGH);  // turn the LED off by making the voltage LOW
                LEDflag = false;
            } else {
                digitalWrite(13, LOW);   // turn the LED off by making the voltage LOW
                LEDflag = true;
            }
        }
    }
}
if ((millis() - timPPG > (1000 / (serialRate / 2) - 10)) && !lcrash) {

    //Serial.print(millis()-timPPG); Serial.print(" ");

    timPPG = millis();

    for (int i = 0; i < 3; i++) {

        //Serial.print(sen[i].aval); Serial.print(" ");

    }

    for (int i = 0; i < 3; i++) {

        if (sen[i].aval == 1) {

            Serial.print(sen[i].IRValue); Serial.print(" ");

            Serial.print(sen[i].RedValue); Serial.print(" ");

            Serial.print(sen[i].GreenValue);

        }

        if (i == 2) {

            Serial.println();

        } else if (sen[i].aval == 1) {

            Serial.print(" ");

        }

    }

}
void loop() {

    // tcaselect(7);
    // accelgyro.getMotion6(&ax, &ay, &az, &gx, &gy, &gz); //read raw accel/gyro measurements from device
    // double accelTemp = accelgyro.getTemperature();

    for (int i = 0; i < 3; i++) {
        if (sen[i].aval == 1) {
            tcaselect(i);
            while (sen[i].obj.available() == false) //do we have new data?
                sen[i].obj.check(); //Check the sensor for new data
            sen[i].IRValue = sen[i].obj.getFIFOIR();
            sen[i].RedValue = sen[i].obj.getFIFORed();
            sen[i].GreenValue = sen[i].obj.getFIFOGreen();
            sen[i].obj.nextSample(); //We're finished with this sample so move to next sample
        }
    }
    delay(5);
}
APPENDIX B

Code for Matlab LSTM prediction of SpO2

clear;
close all;
clc;

load('C:\Users\JoseIgnacio\Desktop\Senior Design\long_breathing_test_vars.mat')
load('C:\Users\JoseIgnacio\Desktop\Senior Design\AC_vars.mat')

figure(1)
plot(GBuff)
hold on
plot(IBuff)

title('IR and Green LED Data')
xlabel('Time')
ylabel('R Ratio')

set(gcf,'color','w')
hold off

cntR = 1;

for counter = 1:40200
if mod(counter,50)==0 && counter > 200

    buffsize = 200;
    [i_ac,g_ac] = ac_g_and_ir( ... 
    totalPPG(counter-buffsize:counter,3),totalPPG(counter-buffsize:counter,1), buffsize,... 
    totalPPG(counter-buffsize:counter,2));
    if g_ac == -1
        g_ac = GACBuff(cntR-1);
    end
    if i_ac == -1
        i_ac = IACBuff(cntR-1);
    end
    GACBuff(cntR) = g_ac;
    IACBuff(cntR) = i_ac;
    cntR = cntR + 1;
end
end
R = totalPPG(:,2);
I = totalPPG(:,1);
G = totalPPG(:,3);

R = R-mean(R)+200;
I = I-mean(I)+100;
G = G-mean(G);

figure(1)
plot(I)
hold on
plot(R)
plot(G,'g')
title('PPG Signal')
ylabel('PPG')
xlabel('Time')
set(gcf,'color','w')

GBuff = lowpass(GBuff,1,100);
IBuff = lowpass(IBuff,1,100);
GACBuff = lowpass(GACBuff,1,100);
IACBuff = lowpass(IACBuff,1,100);
HRBuff = lowpass(HRBuff,1,100);
spo2 = spo2';

muG = mean(GBuff);
sigG = std(GBuff);
\[ \text{muI} = \text{mean(IBuff)}; \]
\[ \text{sigI} = \text{std(IBuff)}; \]

\[ \text{muHR} = \text{mean(HRBuff)}; \]
\[ \text{sigHR} = \text{std(HRBuff)}; \]

\[ \text{muIAC} = \text{mean(IACBuff)}; \]
\[ \text{sigIAC} = \text{std(IACBuff)}; \]

\[ \text{muGAC} = \text{mean(GACBuff)}; \]
\[ \text{sigGAC} = \text{std(GACBuff)}; \]

\[ \text{muspo2} = \text{mean(spo2)}; \]
\[ \text{sigspo2} = \text{std(spo2)}; \]

\[ \text{data}(1,:) = (\text{GBuff} - \text{muG}) / \text{sigG}; \]
\[ \text{data}(2,:) = (\text{IBuff} - \text{muI}) / \text{sigI}; \]
\[ \text{data}(3,:) = (\text{HRBuff} - \text{muHR}) / \text{sigHR}; \]
\[ \text{data}(4,:) = (\text{GACBuff} - \text{muGAC}) / \text{sigGAC}; \]
\[ \text{data}(5,:) = (\text{IACBuff} - \text{muIAC}) / \text{sigIAC}; \]
\[ \text{data}(6,:) = (\text{spo2} - \text{muspo2}) / \text{sigspo2}; \]
dataEnd = data;

numTimeStepsTrain = 700;

dataT = dataEnd(:,1:numTimeStepsTrain);
dataV = dataEnd(:,numTimeStepsTrain:end);

XTest = dataV(:,1:end-1);
YTest = dataV(6,2:end);

XTrain = dataT(:,1:end-1);
YTrain = dataT(6,2:end);

numFeatures = size(XTrain,1);
numResponses = size(YTrain,1);
numHiddenUnits = 200;

layers = [ ...
    sequenceInputLayer(numFeatures)
    lstmLayer(numHiddenUnits)
    fullyConnectedLayer(numResponses)
    regressionLayer];
options = trainingOptions('adam', 'MaxEpochs', 30, 'GradientThreshold', 1, 'InitialLearnRate', 0.001, 'LearnRateSchedule', 'piecewise', 'Verbose', 0, 'ValidationData', {XTest, YTest}, 'ValidationFrequency', 5, 'Plots', 'training-progress');

net = trainNetwork(XTrain, YTrain, layers, options);

% load('net.mat');

[net, YOUT] = predictAndAndUpdateState(net, XTrain);

numTimeStepsTest = size(XTest, 2);

for i = 1:numTimeStepsTest
    [net, YPred(i)] = predictAndAndUpdateState(net, XTest(:, i), 'ExecutionEnvironment', 'cpu');
end
YPred = sigspo2*YPred + muspo2;

YTest = sigspo2*YTest + muspo2;

YOUT = sigspo2*YOUT + muspo2;

YTrain = sigspo2*YTrain + muspo2;

rmse = sqrt(mean((YPred-YTest).^2)/(size(YTest,2)));

accuracy = 1-mean(abs((YPred-YTest)./YTest));

figure(1)

plot([YTrain,YTest])

hold on

idx = numTimeStepsTrain+1:(numTimeStepsTrain+numTimeStepsTest);

plot(YOUT)

plot(idx,YPred,'.-')

rmseStr = sprintf('%0.2f',rmse);

accStr = sprintf('%0.1f',accuracy*100);

title("SpO2 Prediction - RMSE: " + rmseStr + " | Accuracy: " + accStr + ")

ylabel('SpO2')

xlabel('Time(s)')

set(gcf,'color','w')
figure(2)
plot([YTest])
hold on
plot([YPred(1:end-1)])
title("SpO2 Prediction - RMSE: " + rmse + " | Accuracy: " + accuracy)
ylabel('SpO2')
xlabel('Time(s)')
set(gcf,'color','w')

% Program to generate R values

clear all;
close all;
clc;

global coefficient;

coefficient = 1.716*2/3;

s = serialport("COM3",38400);

T = collectData(s);
function [res, ppg] = collectData(s)

buffSize = 200;

val = tic;
pause(1)
num = tic;
sec = (num - val);
tic

numPPGs = 3;
numLEDs = 3;
totalPPG = zeros(1, numPPGs, numLEDs);

counter = 1;
cntR = 1;
flush(s)
while 1
    str = "",
    entry = 1;
    while entry
data = read(s,1,"char");
if (double(data) == 13)
    entry = 0;
    data = read(s,1,"char");
else
    str = str + data;
end
end
new = strsplit(str,' ');
numNew = str2double(new);
if size(new,2)== numNew(1)+1
    if numNew(1) == 4
        temp = numNew(2);
    end
% totalPPG = [totalPPG(2:end,:);numNew(numNew(1):end)];
totalPPG(counter,:) = numNew(numNew(1)-1:end);
tim = tic;
freq = (double(sec)/double(tim - num));
num = tic;
if mod(counter,50)==0 && counter > 200
    [i_ratio,g_ratio,pn_heart_rate] = maxim_heart_rate_and_oxygen_saturation( ...
totalPPG(end-buffsize:end,3), totalPPG(end-buffsize:end,1), buffsize,...

totalPPG(end-buffsize:end,2))

if g_ratio == -1
    g_ratio = GBuff(cntR-1);
end

if i_ratio == -1
    i_ratio = IBuff(cntR-1);
end

GBuff(cntR) = g_ratio;
IBuff(cntR) = i_ratio;
HRBuff(cntR) = pn_heart_rate;

cntR = cntR + 1

figure(1)

uid = uicontrol('Style', 'text','String', ['CNT = ' num2str(cntR+1)], 'FontSize', 80, 
'ForegroundColor', 'b', 'Units','normalized','Position', [0 0 1 1]);

end

counter = counter +1;

else
    end

end
totalPPG = totalPPG(1:end-1,:);
for i = 1:size(totalPPG,1)-1
    m = (totalPPG(i+1,:) - totalPPG(i,:))/4;
    S(i*4-3,:) = totalPPG(i,:);
    S(i*4-2,:) = totalPPG(i,:) + m*1;
    S(i*4-1,:) = totalPPG(i,:) + m*2;
    S(i*4,:) = totalPPG(i,:) + m*3;
end
m = (totalPPG(end,:) - totalPPG(end-1,:))/4;
i = size(totalPPG,1);
S(i*4-3,:) = totalPPG(i,:);
S(i*4-2,:) = totalPPG(i,:) + m*1;
S(i*4-1,:) = totalPPG(i,:) + m*2;
S(i*4,:) = totalPPG(i,:) + m*3;

S = totalPPG(:,4);
A = totalPPG(:,1);

Fs = 25; % Sampling frequency
T = 1/Fs; % Sampling period
L = Fs*totalsecs; % Length of signal
t = (0:L-1)*T; % Time vector

S = S-mean(S);  
A = A-mean(A);  
A = A/5;  
% B = highpass(S,1.2,Fs);  
B = bandpass(S,[1.65 3],Fs);

cnt = 1;

figure(cnt)  
cnt = cnt+1;  
% plot(1000*t,S)  
plot(1000*t,totalPPG(:,1))  
hold on  
% plot(1000*t,B)  
% title('PPG IR Signal - Bandstop Filtered')  
title('X-Axis Acceleration')  
xlabel('t (milliseconds)')  
ylabel('S(t)')  
hold off
set(gcf,'color','w')

Y = fft(S);
P2 = abs(Y/L);
P1 = P2(1:L/2+1);
P1(2:end-1) = 2*P1(2:end-1);
SP1 = P1;
f = Fs*(0:(L/2))/L;

Y = fft(A);
P2 = abs(Y/L);
P1 = P2(1:L/2+1);
P1(2:end-1) = 2*P1(2:end-1);
AP1 = P1;
f = Fs*(0:(L/2))/L;

Y = fft(B);
P2 = abs(Y/L);
P1 = P2(1:L/2+1);
P1(2:end-1) = 2*P1(2:end-1);
P1 = P1;
f = Fs*(0:(L/2))/L;
figure(cnt)
cnt = cnt+1;
plot(f,SP1)
hold on
plot(f,P1)
plot(f,AP1)
title('Single-Sided Amplitude Spectrums of S(t)')
xlabel('f (Hz)')
ylabel('|P1(f)|')
hold off
set(gcf,'color','w')

[a,b] = max(P1);
f(b)*60

res = b;
ppg = totalPPG;
end