Error Prevention in Sensors and Sensor Systems

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ERROR PREVENTION IN SENSORS AND SENSOR SYSTEMS

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

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Pedro Jose Chacon Dominguez
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Abstract

Achievements in all fields of engineering and fabrication methods have led towards optimization and integration of multiple sensing devices into a concise system. These advances have caused significant innovation in various commercial, industrial, and research efforts. Integrations of subsystems have important applications for sensor systems in particular. The need for reporting and real time awareness of a device’s condition and surroundings have led to sensor systems being implemented in a wide variety of fields. From environmental sensors for agriculture, to object characterization and biomedical sensing, the application for sensor systems has impacted all modern facets of innovation. With these innovations, however, additional sources of errors can occur, that can cause new but exciting challenges for such integrated devices. Such challenges range from error correction and accuracy to power optimization. Researchers have invested significant time and effort to improve the applicability and accuracy of sensors and sensor systems.

Efforts to reduce inherent and external noise of sensors can range from hardware to software solutions, focusing on signal processing and exploiting the integration of multiple signals and/or sensor types. My research work throughout my career has been focused on deployable and integrated sensor systems. Their integration not only in hardware and components but also in software, machine learning, pattern recognition, and overall signal processing algorithms to aid in error correction and noise tailoring in all their hardware and software components.
Chapter 1. Introduction

1.1 Motivation

Computational hardware and software capabilities have dramatically increased in what typical sensing platforms can achieve. In various industries and settings, previous systems confined to large and expensive machines can now be implemented into smaller, portable, and even wearable devices for common use. Furthermore, as devices get smaller and more reliable, some uses confined to professional and trained technicians can now be performed by a common person, expanding the capabilities of such devices outside a common clinical, industrial, or any professional setting. Furthermore, with the explosion of data collection, artificial intelligence (AI) and signal processing algorithms have drawn more and more attention in both academia and industry. Examples of such implementation can be observed in countless aspects of everyday life. In deployable consumer electronics such as smartphones and tablets, the implementation of sensors has become more robust and have allowed such devices to be more aware of their surroundings through optical, vibration, geolocation, and many more sensing platforms packaged with the device. Examples can also be observed in dedicated health devices, like Fitbit Bands by Google and Apple Watches by Apple, Inc. For environmental observation purposes, sensors can be integrated into a full characterization platform for objects such as vehicles on a street, or general environmental features such as temperature and humidity. In this work, integrated sensor systems will be observed from their fabrication to their major challenges.

Light based sensors have been the focus of biomedical sensing applications due to their non-invasive nature. If used within a safe spectrum, transmission and reflection of light throughout a sample can yield important information about its characteristics and status. Light applications are based on optical sensing and time measurements of a specific light source to determine aspects
such as distance, temperature, or sample composition among many others.

With an initial focus on biomedical sensing devices, the introduction of an everyday use setting, as opposed to a clinical confined setting, noise and error sources can result from a wide addition of external facets. These include, but are not limited to, noise from motion, misplacement of sensors, and overall conditions of the outside world (i.e., light, temperature, etc.). These do not replace but add to the already inherent error sources in biometric signal devices. Following the same idea, however, the inclusion of additional sensor provides a significant advantage for collaboration and multiple simultaneous signals to recognize and characterize events. Chapter 3 of this work will focus on such biometric sensors implemented in wearable and non-invasive devices. Photoplethysmography (PPG) signal measuring modules, for example, have been a field of extended research because of the constant need to monitor and interpret a heart rate and an oxygen saturation level (SpO2), which are used in a variety of settings such as clinics, operating rooms, home, and even during emergency situations [1-5]. The need for monitoring of PPG signals has transcended typical hospital focused settings into everyday life uses, with an increasing number of people tracking their physical condition with the aid of portable or wearable monitoring modules such as smartphones, smart watches, and activity. Furthermore, PPG signals have been utilized for research in non-invasive calculation of other physiological signals, such as blood pressure and its variation [6-8].

Electrical signals from the brain to different parts of the body have been a main focus of research in recent years. Researchers are trying to fully understand the different electric potential signals that cause organs to act in a certain way. Even if considerable breakthroughs have been made, these signals still contain several key information patterns that are yet to be discovered. Furthermore, simplification of such signals’ acquisition has been a challenge due to the complex
system designs that can only be achieved in large devices in clinical settings. Since relatively same
motion artifacts and noise as PPG can be found in these systems, Chapter 4 is an expansion of
noise reduction and motion artifact tailoring in PPG to additional electrophysiological signals.

Electrophysiological signals (EP) can be taken from different parts of the body for various
purposes. Electrocardiography, or ECG, measures the signal potentials from the heart and can be
used to monitor heart activity and find any potential issues. Electroencephalography, or EEG,
measures brain activity and is commonly used to diagnose brain conditions. Finally,
electromyography, or EMG, measures muscle activity in several parts of the body. signals such
as electrocardiogram (ECG) and electromyogram (EMG).

In addition to various other signals in the same system working together to achieve a more
complete profile of the person using the device, other variations of data can also be obtained. The
direct correlation between light wavelength and skin penetration has been well documented and
studied. Wavelength dependence of the penetration of light on the skin can be exploited by not
limiting the design to a single (or dual) colored light; and instead opting for designs that vary the
wavelength among different colored illumination on the skin. Studies will be performed on inter
and intra correlation between these different colored lights and biological features of the subjects,
through the different PPG signals observed.

The design of custom multicolor illumination sensors will allow for a system that
periodically and systematically switches the current between different colored LEDs. This will
allow for a single wavelength to be measured at one time. While one device is on, the others will
remain off, assuring the elimination of undesired light scattering from other wavelengths. This
scattering can occur because commercial LEDs, even at different wavelengths, can have a minor
percentage of light emission outside of their documented wavelength. Having said this, the creation
of biosensing devices will not only include the light arrays but also the multiplexing circuit and photodetector to switch currents and detect reflected (or transmitted) light, respectively. Furthermore, the research will involve the logic and timing behind this switching and the interpretation of the signals observed.

With the knowledge and experience acquired in the aforementioned sensor networks for biological signals, it was clear that these benefits could also contribute in other industries. In chapter 5, I have expanded such ideas of non-invasive sensing for the fields of construction and traffic monitoring, among others. This is related to the biological sensors in the fact that most utilized components will be highly dependent on timing, and respond to light or other wave interactions. This, along with overall improvements of structure, data handling, and results reporting, will greatly improve the way sensor networks work to evaluate the conditions in the fields mentioned. Similar sensors will also be implemented in a wearable device to demonstrate how their integration is not only limited to larger systems. Furthermore, the problem of limited computing power for such tailoring can be greatly diminished by using a cloud server or an off-site central computer to implement more sophisticated error correction algorithms and pattern recognition of all signals acquired.

1.2 Objectives

The impact and advancements in sensing systems has been presented, with a focus on wearable and non-invasive devices. Furthermore, errors and challenges have also been introduced, presenting an opportunity for improvement using both novel algorithms in software, or implementation of additional channels working in conjunction to address conflicting noise. This will allow for more robust and deployable sensing platforms for a wide variety of applications in commercial and industrial fields. This idea outlines the main objectives of this work, with a full
emphasis on addressing errors and error sources in sensor systems. Complete deployable devices need to be developed with all the aforementioned reliability improvements and evaluated for continuous use. This will prove the importance and benefits of having multiple signals, along with noise correction and error prevention. Solutions for computing power limitations, especially for small form factor and wearable devices, will be proposed and implemented throughout different projects, and will yield various devices for different applications.

1.3 Dissertation Outline

Several topics will be discussed throughout this work, with a focus on full deployable systems. Initial chapters address use of sensor platforms for biomedical and wearable sensors. This is because most of the non-invasive methods for biometric signals, specifically light based, are highly prone to motion and error, which will be greatly benefitted from this work. Starting from a single PPG sensor, the addition of more light colors and more sensing methods for heart activity and muscle activity will be addressed on the same device and use the software and hardware solutions proposed.

In latter sections, the idea of multiple sensor systems is expanded upon other applications. Such applications include vehicle profiling in highways, and ambient sensor networks in deployable, wearable sensor devices. With such abundance of data, solutions to properly analyze them are presented through the use of cloud computing and signal processing. Multi-signal processes to address errors and noise are further presented, such as redundancy and constant calibration, to further increase accuracy and create reliable sensor networks. Finally, conclusions and a summary of work will be presented, with inherent challenges for all aforementioned systems discussed. In particular, power solutions are recommended with a focus on conservation and harvesting of energy. This is a highly important aspect of such devices, given their inherent
continuous and automatic handling of data. Furthermore, their location and use (i.e. outdoors and wearable) yield possibilities for energy harvesting from external sources such as motion and/or sunlight.
Chapter 2. Background

2.1 Pulse Oximetry

Pulse oximetry is a non-invasive measurement method of measuring oxygen saturation (SpO2) in an arterial blood vessel [10]. The oxygen saturation is defined in (1). Hb and HbO2 are the concentration of deoxygenated hemoglobin and oxygenated hemoglobin, respectively, such that

\[ \text{SpO}_2 = \frac{\text{HbO}_2}{\text{Hb} + \text{HbO}_2}. \]  

(1)

Figure 2.1 (a) illustrates the basic operation principle of the pulse oximetry using a reflectance-based probe. In transmission mode, light emitted from light emitting diodes (LEDs) on the top surface of the skin travels through the tissue and is detected at the bottom of the skin surface by a photodetector. The Beer-Lambert’s law describes the attenuation of the transmitted light during the operation, such that

\[ I = I_0 \exp(-\varepsilon c d), \]  

(2)

where \( I \) is the intensity of the transmitted light, \( I_0 \) is the incident light intensity, \( \varepsilon \) is the extinction coefficient, \( c \) is the concentration of the medium, and \( d \) is the traveling distance of the light. In this case, further assumption for (2) concludes that the light source is monochromatic, and no scattering occurs. However, human tissue has multiple layers (\( N \)) of different absorbers, including arterial and venous blood vessels. Accounting for all the different layers, the total light intensity (\( I_{\text{total}} \)) can be defined as

\[ I_{\text{total}} = I_0 \exp(-\sum_{i=1}^{N} \varepsilon_i c_i d_i), \]  

(3)

where \( i \)-th layer has extinction coefficient (\( \varepsilon_i \)), concentration (\( c_i \)), and thickness (\( d_i \)).

With each cardiac cycle, as shown in Figure 2.1 (b), the blood volume of the arterial vessel’s changes, increasing during the systole and decreasing during the diastole (systole = diastole + \( \Delta d \), where \( \Delta d \) represents the change in the artery diameter caused by volume fluctuations); whereas
blood volume in other tissues remains relatively constant. The relevant static components are the
tissue, venous, capillary, and non-pulsating arterial blood. The only varying component is the
arterial blood. The pulsating arterial vessel corresponds to the AC component and the relevant
static components correspond to the DC components as shown in Figure 2.2. From (3), we can
now separate light attenuation from static components and varying component at each cardiac
cycle as

\[ I_{Diastole} = I_0 \exp(-\varepsilon_{static} c_{static} d_{static}) \times \exp(-\left(\varepsilon_{HbO2} HbO_2 + \varepsilon_{Hb} Hb\right)d_{diastole}) = I_{AC} \]

and

\[ I_{Systole} = I_0 \exp(-\varepsilon_{static} c_{static} d_{static}) \times \exp(-\left(\varepsilon_{HbO2} HbO_2 + \varepsilon_{Hb} Hb\right)d_{systole}) = I_{DC} \]

The calculation can be further simplified by dividing IAC by IDC, followed by taking the natural
logarithm to yield

\[ \ln \left( \frac{I_{AC}}{I_{DC}} \right) = \Delta d (\varepsilon_{Hb} Hb + \varepsilon_{HbO2} HbO_2). \]  

(6)

Figure 2.3 shows the difference in the light absorption coefficient of oxygenated hemoglobin
(HbO2) and deoxygenated hemoglobin (Hb) as a function of the wavelength. The highest
absorption ratio of deoxygenated hemoglobin (Hb) and oxygenated hemoglobin (HbO2) is at 660
nm (\(\lambda_1\)) and the lowest is at 940 nm (\(\lambda_2\)) [11]. With two different wavelengths, 660 nm (\(\lambda_1\)) and
940 nm (\(\lambda_2\)) can eliminate \(\Delta d\) when (6) is divided by each wavelength case yielding ratio R,

\[ R = \frac{\ln \left( \frac{I_{AC(\lambda_1)}}{I_{DC(\lambda_1)}} \right)}{\ln \left( \frac{I_{AC(\lambda_2)}}{I_{DC(\lambda_2)}} \right)} = \frac{\varepsilon_{Hb}(\lambda_1) Hb(\lambda_1) + \varepsilon_{HbO2}(\lambda_1) HbO_2(\lambda_1)}{\varepsilon_{Hb}(\lambda_2) Hb(\lambda_2) + \varepsilon_{HbO2}(\lambda_2) HbO_2(\lambda_2)}. \]

(7)

Therefore, we can calculate SpO2 by substituting Hb and HbO2 variables from (1) and simplify
as

\[ \text{SpO}_2 = \frac{R \varepsilon_{\text{Hb}}(\lambda_2) - \varepsilon_{\text{HbO}_2}(\lambda_2)}{R(\varepsilon_{\text{Hb}}(\lambda_2) - \varepsilon_{\text{HbO}_2}(\lambda_2)) + \varepsilon_{\text{HbO}_2}(\lambda_1) - \varepsilon_{\text{Hb}}(\lambda_1)}. \]  

(8)

The relation between R and SpO2 needs to be corrected due to the light scattering effect caused by the non-uniform property of the tissue, as shown in Figure 2.1. Furthermore, an empirical linear or quadratic approximation can be implemented through a calibration process relating the ratio R to the actual SpO2 measurement. In the reflectance mode, the reflected light and scattered light are collected, and the resulting pulsation signal can be successfully used to calculate the oxygen level of a subject [9, 34].

Figure 2.1 (Top) Illustration of reflectance-type oximetry operation. LEDs and a photodetector are on the same side for a wearable application; and (bottom) illustration of blood vessel system with each heartbeat
2.2 Wearable PPG Sensors

Photoplethysmography (PPG) is a basic principle of non-invasively measuring the heart rate and the oxygen level across a human body. There are two important factors related to the PPG measurement: volumetric analysis and absorption coefficient differentiation. The PPG Principle is based on the Beer Lambert’s law, which relates light attenuation through a sample with the properties of the sample itself. The PPG principle states that the optical properties of the tissue and the blood can be characterized by utilizing light sources (e.g., light emitting diodes) and a photodetector (e.g., a photodiode). The light intensity changes when the volume of the arterial
vessel changes during the systolic phase, which is the blood ejection phase of the cardiac cycle. The variation of the light intensity is converted into electrical signal and amplified, sampled, filtered, and recorded.

Transmittance-type pulse oximeters are currently being sold and marketed for home use, and can indicate heart rate and oxygenation levels with high accuracy. These devices are placed on a patient’s extremities with a clip-on design, with the light sources on one side of the clip and the photodetector on the other. This placement, while optimal for a wide variety of applications, can cause limitations for potential placement and extended uses. Low ambient temperature can lead to a contraction of human arteries that reduces heat loss and retains body temperature. In this case, arterial capillaries show lower signal levels and potentially reduce the accuracy of the measurement.

Reflectance-type pulse oximeters can address this issue, since the probe can be deployed at nearly any place on the body [9]. This is due to the photodetector, which in this case records the intensity of scattered or reflected light, being placed near the light sources on the same side of the probe. Consequently, the sensor can be attached closer to the heart area which gives more immediate oxygen level of the subject compared to the oxygen level readings from extremities. The measuring and processing algorithms to analyze these signals are done locally using a microcontroller that is limited to a single function. Having a one-sided probe, however, and with the inclusion of an optical based method, greatly increases the sources of motion noise, hence increasing the need for a solution on how to efficiently remove such noise and signals that distort the readings being taken.

2.3 Noise and Motion Artifacts

While optical methods are a viable method to non-invasively measure the intended
parameters, these highly prone to noise from surrounding environment light and minimal to high motion artifacts. Consequently, continuous oximetry devices need to take motion into consideration, especially reflectance type based, and be robust to any motion artifact to accurately measure and present results. For this purpose, we implement novel data-dependent motion artifact tailoring algorithm that continuously eliminates noisy data caused by the subject’s motion and measures oxygenation level with high accuracy in a continuous, real-time manner.

To overcome computing limitations, the system has been developed to obtain PPG signals and send them wirelessly to a much more capable device (such as a smartphone or smart watch) in order for it to perform signal processing and interpretation with minimal delay.

A proven and published motion tailoring algorithm [10] has created highly desirable outcomes for removing motion artifacts from PPG signals. In this work, I present a method to remove motion artifacts, tailor the signal, and extract significant data for a variety of measurements in real time. Furthermore, this algorithm integrates the resulting tailored signal with additional steps and presents a continuous and responsive SpO2 reading while motion artifacts are being applied. With the help of our complete system integration, these calculations can be performed in real time, further resulting in improved response times and increased accuracy.

Advancements towards fully wearable SpO2 sensors, as demonstrated in [11-12], can benefit from motion artifact tailoring in order to achieve significantly higher accuracy in real time and reach additional functionalities. While the modular system allows for ease of testing and upgradability, a fully integrated device that uses the most recent chipsets and advances in pulse oximetry can benefit even further from this implementation and motion tailoring algorithm.

EP signals are extremely sensitive to motion artifacts (MAs) caused by the subject’s movement [13]. In order to properly process a PPG signal, for example, for heart-rate or blood-
oxygen level (SpO2) monitoring, it is necessary to detect and remove the MAs from the PPG raw
signal. Many existing research works have been dedicated to this problem. A major approach is
the independent component analysis (ICA) [14], [15]. Time- or frequency-domain based ICA
algorithms were employed to find the signal subspace for eliminating/mitigating the MAs.
However, the required assumption that the desired signal and the MAs are completely uncorrelated
is not valid, especially for PPG signals [16]. Another commonly-adopted approach is the adaptive
noise cancellation (ANC) [17–19]. In the ANC approach, one first needs to acquire the reference
signal. As a matter of fact, the ANC approach has a major drawback that its performance relies
heavily on the quality of the estimated reference signal. When the estimated reference signal is not
reliable, the ANC performance can be very poor. Auxiliary data acquired from the acceleration
meter can also be utilized for the MA removal. For example, a spectrum subtraction technique was
proposed to suppress MAs in the spectral domain [20-21]. However, these data (a.k.a. acceleration
data) can reflect only three-dimensional movements of the subject, but the MAs are often generated
by the abrupt distance changes between the oximeter and the subject’s skin. Hence, the acceleration
data alone cannot represent all kinds of MAs in PPG signals. Recently, a method called TROIKA
was proposed for tracking the heart rates when the subject is exercising [22]. The TROIKA
approach is suitable for regular and frequent MAs caused by the subject’s running or respiration.
Nevertheless, the abrupt or aperiodic MAs would often cause significant performance degradation
of the TROIKA scheme.

2.4 Multi-Signal and Multi-Channel Systems

Multiple wavelength approaches have been utilized before [23-25] to calculate several
physiological parameters, such as pulse transit time and estimating blood pressure changes in real
time. These show how all PPG signals from different wavelengths can be observed in real time.
For our approach, we can apply both of our MA tailoring and authentication algorithms on each signal, which will greatly increase the accuracy and reliability in these systems. Diagnoses, such as sleep apnea and others are currently limited to expensive and/or clinically based systems. With increased reliability and accuracy, a wearable and home use system is possible, and we believe can significantly change the potential of such devices.

2.5 Sensor Network for Traffic Profiling

Relatively low vertical clearance under bridges, overpasses, and other road construction work platforms pose significant collision threats for crossing vehicles, especially if they exceed such height by a small margin due to incorrect loading or inherent vehicle height. These vehicles will be referred to as overheight vehicles moving forward. This has resulted in collisions and accidents that lead to severe damages to both vehicles and structures. As it is to be expected, these damages go beyond the structural, but can also entail physical injuries to individuals and significant monetary costs for repairs and/or medical expenses.

Between the years of 1987 and 1992, for example, the Texas Department of Transportation (TxDOT) reported 241 collisions due to overheight vehicles [1]. In the state of Maryland, and out of the 1,496 bridges susceptible by such collisions, about 20% were stuck and 58 required repairs between the years of 1995 and 2000, as reported by Fu et al. in 2004 [4]. In this same report, it is mentioned that out of 29 reported states, 18 indicated that these overheight collisions are, in fact, significant problems due to the aforementioned consequences. These results have also been discussed at a nationwide level and how they have resulted in injuries, damages, and even fatalities [3-4], without mentioning additional problems such as construction time, road blocking, and other delays that may affect third parties overall.

The most logical approach to this issue is to focus on the prevention of such accidents to
avoid their consequences. Several researchers have decided on focusing on two different aspects of such prevention. First of all, addressing and analyzing vehicle height to determine when a vehicle is too high for an upcoming obstacle. Furthermore, they focus on alerting the driver of an overheight vehicle of this detection well in advance and in time for them to act, such as taking an upcoming alternative route or return to avoid a collision. Several criteria need to be met for the purpose of accurate collision prevention. Detection must be accurate enough within a wide range of vehicle speed, and fast enough to send information to a warning signal and alert the overheight vehicle driver.

In a report by Agrawal in 2011 [4], several of these systems were assessed through surveying and common issues arose in key areas of overall functionality, accuracy, and cost. Red and infrared (IR) light emitting diode (LED) lights for time of flight (ToF) sensors are observed throughout. These sensors show satisfactory results in most cases under ideal conditions, with errors and false positives caused by environmental conditions. These can range from weather (i.e., snow, hail, rain, etc.), traffic (i.e., parallel cars driving and excess speed), and other sources such as birds crossing and dust infiltration in sensors. The other main common issues observed in these cases are direct results of their installation setup. For example, the fact that they are installed in the sides of roads means that two vehicles driving side by side in a multi-lane road can yield false alarms if one of the vehicles does not exceed height limitations. Additionally, installation and maintenance yielded high cost due to their complex setups and access for workers to provide service, especially in busy intersections and highways.

Cameras and light sensors are commonly used for addressing vehicle classification, profiling, and overheight sensing, with varying results [5-8]. In particular, time of flight (ToF) distance/range sensors can be used to calculate vehicle profiles. These sensors show satisfactory
results in most cases under ideal conditions, with errors and false positives caused by environmental conditions ranging from weather (i.e. snow, hail, rain, etc.), traffic (i.e. parallel cars driving, excess speed), and other sources such as birds crossing and dust infiltration. Issues observed in these cases are also direct results of their installation setup as well. For example, some are installed in the sides of roads, meaning that two vehicles driving side by side in a multi-lane road can yield false alarms if one of the vehicles does not exceed height limitations.
Chapter 3. PPG and Motion Noise Removal

3.1 Introduction

As a starting point for sensing platforms and how they are affected by noise, a wearable pulse oximeter for continuous and real time monitoring is presented in this design. As previously mentioned, pulse oximetry is light based, so significant noise and errors can be introduced on wearable devices of this kind, resulting from movements, skin color, and many sources discussed later in the chapter. This work was performed in collaboration with the Department of Kinesiology at LSU, with the help of Dr. Brian Irving for testing subjects and analyzing data. For motion artifact tailoring and signal processing, this work was performed in collaboration with Dr. Hsiao-Chun Wu and Dr. Limeng Pu from the Electrical Engineering Dept. at LSU.

The size profile and reflectance type of the design enables the system to be wearable and placed seamlessly with no discomfort where the signal needs to be taken. By taking advantage of current wireless transmission and signal processing technologies, the pulse oximeter can successfully capture the measured signals and send them wirelessly to a mobile device application for processing. Furthermore, a novel data-dependent motion artifact (MA) tailoring algorithm is presented to eliminate noisy data due to the subject’s motion and measure oxygenation level with high accuracy in real time.
3.2 Design and Fabrication

The pulse oximeter system is divided into two main circuits that work together to fulfill the measurement principle described above. The first component (detailed in Figure 3.1(a)), referred to as the LED driving circuit, is in charge of driving both red (OSLON SSL v1.3,) and infrared (OSLON Black Series v1.5) LEDs, as well as indicating the sensor when a reading is to be taken. The second component (detailed in Figure 3.1(b)), or the data acquisition (DAQ) circuit, is in charge of reading reflected light through a high-resolution silicon photodiode (Thorlabs FDS100). Finally, it is in charge converting it to a digital signal, and sending it for analysis. Both components work in a synchronized manner in order to obtain the signal with the highest intensity (peaks of the LED intensities), thereby obtaining the highest quality signal.
Figure 3.2 Representation of the completed design with: (a) two sensor heads; (b) the various PCB boards included inside, and (c) placement of all sensors for testing and calibration purposes.

All individual systems have been made in 48 mm by 18 mm interchangeable, modular boards that can be stacked on top of each other, as seen in Figure 3.2(a). This allows the system to be considerably compact and portable. Furthermore, upgrades to individual systems can be made without redesigning or refabricating the entire device.

The LED driving circuit is an adjustable switching current source, which applies square waveform to red (wavelength: 660 nm) and infrared (IR, wavelength: 940 nm) LEDs. Frequency, duty cycle, and current of LEDs are adjustable independently based on the application. The standard set onward was a duty cycle of 50%, and 100Hz PWM signal to drive both LEDs. The resulting data rate due to switching between both LEDs and sending data through the Bluetooth module was 50Hz.
This circuit is composed of three compartments, as seen in Figure 2.4, and each of them have a specific function: signal generation; duty cycle adjustment, and current source. The signal generator circuit generates square waveform to drive the LEDs. The Duty cycle adjusting circuit adjusts the percentage of the time in which the LEDs will be on. The output of the signal generator is directly applied to the duty cycle adjusting circuit of the red LED and the inverted signal of the signal generator is applied to the duty cycle adjusting circuit of the IR LED. This allows independent readings of each wavelength with the same photodetector. Moreover, this part of the circuit provides two synchronous signals to the receiver circuit to indicate which LED is turned on at the moment. Finally, the current source circuit is needed to sink a regulated and adjustable current from LEDs. There is one current source circuit for each LED as the final stage of the circuit. In board potentiometers can set the current between 100 mA to 700 mA. In this circuit, the current is set to 300 mA for red LED and 200 mA for IR LED when they are turned on, with a supply voltage of 3.3 V. An estimated power consumption of the overall system, including LEDs, microcontroller, and Bluetooth devices, is in the range of 450-530 mW.

This data acquisition system is composed of three fundamental blocks: the current reader system; the sensor driver, and the control unit. The control unit used is a low power, commercially available microcontroller (Arduino Nano, ATMega328), which communicates with any smartphone through a Bluetooth module (HC-05) and serial communication (Baud Rate 115200, 8 data bits).

A trans-impedance amplifier converts the output current from the photodiode to a desired voltage range. The output voltage is measured by an analog to digital converter and the value is sent to the smart phone using the Bluetooth module. A photodiode sensor driver consists of a feedback resistor, which determines the device sensitivity, and it limits the maximum current
which can be measured by the system; therefore, the feedback resistor value can be chosen in accordance with the photodiode current range and desired resolution. To get maximum intensity readings, synchronization PWM signals are provided by microcontroller and sensor driver for the LED driver circuit, which determines the frequency and duty cycle that each LED is on. The output current of the photodiode is sampled at the middle of the high state of each PPG signal.

Additional components in the device include a battery and a 6-pin connector to attach the sensor head. As mentioned before, all systems, including the microcontroller and Bluetooth module, are stackable and interchangeable.

After the PPG signal is digitalized and transmitted over Bluetooth to a smartphone, a customer-made APP displays the signal waveform in real time as well as detects the motion artifacts using the algorithm described later on in Section IV. The motion-artifact-tailoring algorithm is implemented in a high-level language such as MATLAB and then ported to the Android Application.

3.3 Signal Processing

Because motion artifacts cause serious problems in the PPG signal processing, the detection and elimination (or mitigation) of motion artifacts are obviously crucial when the PPG signals are used to measure the biological information. We have developed a custom tailoring algorithm for such events, which has been studied and detailed in our previously reported work [10]. In the proposed new motion-artifact tailoring method, the motion-artifact detection consists of three major stages: (i) optimal window-size determination, (ii) short-time variance extraction, and (iii) transition detection. Usually the PPG signal waveforms appear to be very different across subjects, the subject-independent window-size (constant short-time window-length) is surely non-optimal when one needs to acquire robust variance features later on. In fact, the optimal window-
size should be “subject-dependent”, which means it depends on the individual subject’s signal characteristics. Here a new unsupervised (no training is necessary) subject-dependent window-size determination technique is adopted to search for the “optimal” window-size. A robust feature, or short-time variance, is utilized in this work for motion-artifact detection because the associated computational burden is very light. At last, the transition points (at which there appears to be a change from the regular signal to the motion artifact or vice versa) can thus be located by comparing the short-time variances with an appropriate threshold.

Once the artifact intervals are spotted accordingly, the corresponding signal data can be tailored (eliminated completely) from the original (raw) signal waveform. The proposed motion-artifact tailoring algorithm is introduced as follows.

### 3.3.1 Feature (Short-Time Variance) Acquisition

The short-time variance is the underlying feature for motion-artifact detection. The short-time variance, which is a function of window-size $M$, can be formulated as the result from a mapping from the original PPG signal sequence $x(n), n = 0, 1, 2, \cdots$:

$$x(n) \xrightarrow{\text{yields}} Y_{\mu}^M(m), m = 0, 1, 2, \cdots, \quad (1)$$

where

$$Y_{\mu}^M(m) \eqdef \frac{1}{M-1} \sum_{n=m_{\mu}}^{m_{\mu}+M-1} \left[ x(n) - \bar{x}_{\mu}^M(m) \right]^2, \quad (2)$$

$n$ denotes the original signal sample index, $m$ denotes the sliding-window index, $\mu$ denotes the window forward size, and

$$\bar{x}_{\mu}^M(m) \eqdef \frac{1}{M} \sum_{n=m_{\mu}}^{m_{\mu}+M-1} x(n). \quad (3)$$

How to determine the optimal window size $M$ will be presented next.
3.3.2 Optimal Window-Size Determination

According to my collaborator’s experience in ultrasonic signal processing (see [35]), a nonlinear program can be facilitated to find the optimal window size $M$. The “smoothness” of the variance sequence $\gamma^M_\mu(m)$ is the objective function while the “compact-support” requirement corresponds to the nonlinear constraint. The compact-support requirement implies a steep-transitioned variance sequence $\gamma^M_\mu(m)$. For ultrasonic multiridge detection, a kurtosis function $\kappa[\gamma^M_\mu(m)]$ was proposed in [14] to define such a constrained optimization problem.

Define

$$p_m \equiv \frac{\gamma^M_\mu(m)}{\sum_q \gamma^M_\mu(q)}, \quad (4)$$

$$\mathcal{M} \equiv \sum_m [(m-1)\mu + 1] p_m, \quad (5)$$

and

$$\mathcal{A}_k \equiv \sum_m [(m-1)\mu + 1 - \mathcal{M}]^k p_m, \quad k = 2, 4. \quad (6)$$

According to [15], the kurtosis of the short-time variances $\gamma^M_\mu(m)$ is formulated as

$$\kappa[\gamma^M_\mu(m)] \equiv \frac{\mathcal{A}_4}{\mathcal{A}_2^2}. \quad (7)$$

Note that $p_m$ sequence in (4) can satisfy the probability axioms [36].

It is proved in [35] that $\kappa[\gamma^M_\mu(m)]$ is $\mu$-multiple-shift invariant. That is, one can start a sliding window to sample data at any time instant and the optimal window-size will still remain the same. In other words, our method is resilient against the onset ambiguity. Define the kurtosis-sensitivity with respect to $M$ as
\[ S(M) \overset{\text{def}}{=} \max_m \frac{|y^M(m) - y^2_M(m)|}{\gamma^M(m)}. \]  

(8)

According to (1)-(8), the optimal window-size \( M \) can thus be determined from the following nonlinear program:

\[ M^{\text{opt}} = \max (M) \]

subject to

\[ S(M) < \varrho, \]

(9)

where \( \varrho \) is a pre-set upper-bound for the kurtosis-sensitivity constraint function.

3.3.3 Transition Detection and Motion-Artifact Tailoring

After the optimal window-size is determined according to (9), the detection of motion artifacts can take place thereby. After the detection of segments pertinent to motion artifacts is carried out throughout the entire PPG signal sequence, we denote the collection of the detected transition-points (the occasions of the transitions from the regular signal to a motion artifact and vice versa) by \([t_1, \tau_1], [t_2, \tau_2], ..., [t_i, \tau_i], ...\). Thus, we can represent the \( i \)th detected motion-artifact signal segment \( \Omega(n) \) by

\[ \Omega_i(n) \overset{\text{def}}{=} \begin{cases} x(n), & t_i \leq n \leq \tau_i, \\ 0, & \text{elsewhere} \end{cases}. \]

(10)

Note that when \( \Omega_i(n) = x(n) \), the corresponding signal samples carry “useless” information (or no measurement should be taken at the corresponding time instant \( n \)). Therefore, the “tailored” signal sequence \( x'(n) \) can be expressed as

\[ x'(n) \overset{\text{def}}{=} x(n) - \sum_i \Omega_i(n). \]

(11)
If we convert (tailor) $x(n)$ to $x'(n)$, the original waveform of the PPG signal can be preserved but other existing spectrum-based methods fail to do so. When $x'(n) = 0$, the PPG signal is tailored or eliminated, such zero-valued signal samples $x'(n)$ should be thrown out without any further use. That is, one should “stop” sampling the motion-artifact segments because no accurate information can be extracted from those data. Henceforth, the tailored signal sequence $x'(n)$ can be further processed for the fast SpO2 computation in addition to the heart-beat rate tracking and other relevant physiological information-retrieval.

3.4 Results

3.4.1 Experimental Setup

Because motion artifacts A total of 8 subjects who provided written and informed consent approved by the Louisiana State University’s Institutional Review Board were tested under the following conditions to examine the accuracy of our device, plus the benefits of the motion tailoring algorithm when compared to the other commercial and available clinical devices. For the purpose of calibrating and evaluating the system, healthy men and women between 18-40 years of age were recruited and studied. Furthermore, individuals with self-reported cardiovascular disease, type I or II diabetes, or any metabolic diseases were excluded. Women who self-report being pregnant were also excluded from the experiments.

In this protocol, subjects were asked to sit quietly during all error calculation measurements. Motion application throughout testing was applied both randomly and in specific periods of time (5 seconds interval). This motion consisted of various index and thumb finger movements with the intent to press, slide, and separate the sensor, or photodetector, against the surface of the skin. Normal activity and movement are expected to result in the same types of motion artifacts, mainly sliding and pressing to and from the surface of measurement, and can be
applied in various different locations, with varying intensities. We decided that comparisons would be made between sensors placed on the same fingers, but in opposite hands. While having a larger pool of subjects will allow for randomized placement, the setup utilized made consistent placement and simultaneous comparisons easier in order to obtain more accurate results from the subjects available.

Figure 3.3 Demonstration of device and the observed waveforms in the tablet device. The currents in µA from the Red (top) and IR (bottom) LEDs are plotted against time.

Table 3.1 The average SpO₂ percentage error before and after MA Removal

<table>
<thead>
<tr>
<th>Subject</th>
<th>Error Before [%]</th>
<th>Error After [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.005</td>
<td>1.001</td>
</tr>
<tr>
<td>2</td>
<td>6.654</td>
<td>1.109</td>
</tr>
<tr>
<td>3</td>
<td>3.953</td>
<td>0.791</td>
</tr>
<tr>
<td>4</td>
<td>4.013</td>
<td>0.803</td>
</tr>
<tr>
<td>5</td>
<td>3.789</td>
<td>0.758</td>
</tr>
<tr>
<td>6</td>
<td>3.247</td>
<td>0.812</td>
</tr>
<tr>
<td>7</td>
<td>3.238</td>
<td>0.810</td>
</tr>
<tr>
<td>8</td>
<td>3.236</td>
<td>0.809</td>
</tr>
<tr>
<td>Average</td>
<td>4.426</td>
<td>0.862</td>
</tr>
</tbody>
</table>
Response time and accuracy in heart rates were also observed against previous studies on commercial devices, such as the Apple Watch Series 1 and Fitbit Blaze, from Fitbit, Inc. and Apple, Inc., respectively [18-21]. Changing heart rate values were observed in our system, from which response times and average calculation windows were compared to those of commercial devices reported by previous studies [18-21]. This is important because the window used for average values, specifically of heart rate, directly influence how fast the device will react to events causing increases or decreases in heart rate.

Furthermore, a personal clip pulse oximeter (VOL600, Volmate, Inc.) was utilized to evaluate and compare changes in SpO2. These measurements were done by observing the screens of such devices and recording every five seconds or when a change in the value happened. The custom sensor heads were placed on the subject’s index fingertip and wrist. The Bluetooth module of the system provided the interface between analog circuitry and the display. In this case, the display utilized was an Android based tablet (Samsung, Inc.) with a custom application developed to properly display not only the PPG signal but also the resulting measurements. Additional options for filtering and display were added to the application for additional functionality, as shown in Figure 3.3.

To calculate the accuracy and evaluate the response time of our design, a clinical and continuous oximeter system (OXY200, Biopac Systems, Inc.) with a transmittance-based probe was utilized. This system was set up to measure heart beat rate and blood oxygenation at a rate of 50 Hz, without adding any motion (true ground measurement). To calculate error, the subjects wore both devices at the same time, but motion artifacts were only applied manually (pressing and sliding) to our tested device. The clinical device remained at rest, and the standard error was calculated between the raw signal and clinical reading and between the tailored signal and critical
reading. The clinical device was kept at rest in order for more precision on the accuracy calculations, and thus the difference in response times were negligible, as no sudden changes occurred in SpO2 and/or heart rate measurements. Furthermore, these clinical readings at rest were utilized for our calibration, relating SpO2 readings to the R-values measured by our sensor. Testing and calibration using fingertip were performed on all subjects independently, and error was calculated against the clinical device placed on the fingertips.

An expansion on the aforementioned protocol has been approved, aiming to test the subject under more natural circumstances (i.e. walking, running, and daily activities) and simulating changes in elevation in order to achieve a wider range of blood oxygen levels. In this case, however, we have opted to test in a controlled environment in order to better compare with the

Figure 3.4 PPG signal with motion artifact instances (top) and overall improvement of the R-value curve after MA removal (bottom). Open circles represent R-values calculated under MA, which were removed by the tailoring algorithm and replaced by the R-value trend value.

An expansion on the aforementioned protocol has been approved, aiming to test the subject under more natural circumstances (i.e. walking, running, and daily activities) and simulating changes in elevation in order to achieve a wider range of blood oxygen levels. In this case, however, we have opted to test in a controlled environment in order to better compare with the
clinical devices and, consequently, determine the overall improvement in accuracy and reduction in error. Artificial noise during rest allows for a more accurate comparison and evaluation of accuracy, given by the fact that most clinical devices are meant to be used under such conditions, and that observation can be made with ease to determine where noise began and ended to validate our algorithm (as shown in figure 3.4, for example). It was determined that we would simulate motion that is most common while running and walking, as well as other exercises that induce separation and sliding on the area where the measurement is being taken. However, the intensity of such simulated motion covers a wider range of intensities, from lower (i.e. tapping, harder to identify), to higher ranges (i.e. sliding, easier to identify but harder to eliminate without affecting the final result). Higher ranges prove beneficial when evaluating the true performance of our method and how it improves results from the same PPG signals.

3.4.2 Performance Metrics and Evaluation

The system was developed for all the different parts mentioned before and shown in Figure 3.2. Figure 3.3 represents the custom Android application, displaying both IR and red PPG signals on two separate plots, as well as the resulting measurements calculated after motion artifact removal. Furthermore, the controls for signal processing are on the user interface (UI) that allows the user to customize what is being observed and additional filtering of the signal. The three main components, as shown in the UI, work together to obtain, filter, and send the signal in a real-time manner.

Given the nature of the circuit and the minimal number of channels it actually uses; it is possible to miniaturize the device to much smaller dimensions in order for a more seamless wearable device. The sensor head size and form factor provide an increased freedom of placement, using custom mounts that will depend in the application desired. This placement, as previously
mentioned, is not limited to specific regions of the body and can provide additional benefits and applications.

Raw data were obtained under random motion and processed with the proposed motion artifact algorithm to determine all the instances of motion. As demonstrated in Figure 7, all instances of motion on the raw signal are identified from beginning to end. Because this data is corrupted with motion artifacts, it would degrade the calculation of the oxygen level. Therefore, this section of data is discarded from final calculations, and replaced by the most recent trend line being followed.

Motion can cause outliers and incorrect readings in the R-values, yielding incorrect results in the SpO2 readings of any device. For this reason, once our device has removed such motion signals, the outlying R-values are eliminated from the calculation, thereby significantly reducing reading errors. Throughout the device’s functionality, the system continuously tracks and stores the trend line, or baseline, of the R-values with no motion artifacts. This is done through spline fitting, and is further utilized to replace removed R-values in motion detected regions in the final SpO2 calculations. Figure 7(b) symbolizes an example of how the R-value trend changes after removing the motion artifacts. The majority of the outlying R-values obtained are removed from the signal and replaced by baseline values, resulting in more accurate measurements of oxygen level.

It is important to point out that the algorithm was performed under real-time conditions, and no post processing was made to detect and remove motion from the raw signals. Additionally, however, we have included functionalities in the android application for user experience purposes, such as highlighting motion affected areas. Post-processing was performed with the sole purpose of comparing and evaluating the accuracy of our methods, including accuracy and error before and
3.4.3 Accuracy Results

After the signal was tailored, we observed an overall improvement of the measurement accuracy, even with a constant motion, when compared to the continuous clinical device (OXY200, Biopac Systems, Inc.). Figure 8 represents the overall trend of several subjects throughout a testing period, when compared to the OXY200 clinical device being worn on the fingertip. The standard error calculated for all subjects was between 0.7-1.1 SpO2%. The changes in oxygen level observed are due to several breathing stages (i.e. holding breath and breathing at...
different rates) that affected the reading to evaluate the functional range of the devices. Furthermore, overall improvement within the same device, before and after motion artifact tailoring was observed (see Table 3.1).

Due to the reflectance-based and continuous measurement, more immediate information and can be perceived by our device, when compared to other existing ones. This can be observed in Figure 3.5, where measurements from our device are compared against measurements of the clinical system for three separate subjects. As defined in the IRB protocol, motion was applied throughout the testing of these subjects in a period of 5 seconds. Motion applied included sliding and pressing of such device to and from the surface of the skin. Faster responses were observed in the graphs overall, as indicated by earlier rises and falls of oxygen level in subjects. This is due to the optimal window for calculating and extrapolating both heart beat and oxygen level. The OXY200 system, although measuring at a high sample rate, constantly rounded its results to the nearest whole numbers, which further impacted its slow response time, especially when compared to our system. Response time was carefully observed in the OXY200 and the commercial clip device for SpO2. Both clinical and commercial device use a fixed time window to calculate average SpO2 measurements. Our device, on the other hand, uses a smaller window, as defined by our motion tailoring algorithm. This resulted in an observed 5-15 second faster response time to changes in the PPG waveform due to changes in oxygen saturation.

Finally, using the tailoring algorithm, in conjunction with our peak detection algorithm, heart rate was also calculated by utilizing the rising peaks of the same PPG signal measured. As described in [10], the resulting error-percentage for this measurement was between 1.32 to 4.45%. For heartbeat measurements, and for the same reason as the clinical devices, commercial devices have been reported to update every 15-60 seconds [37, 38], with a significantly lower response
rate than our proposed device. These indicate that the values are not fully quantified in real time, but are averaged over a long period, highly filtering the data and only showing a current value when a highly stable signal was obtained from the subject’s wrist.

### 3.5 Conclusions and Discussion

An electronic system was designed to measure the oxygen level in blood in a non-invasive, continuous manner. The system utilizes the reflective method for measuring light intensity, which offers the advantage of one-side contact between skin and LEDs. Moreover, the system is portable and may be applied to measure the oxygen level in various low noise areas of a subject such as their neck or chest.

With inherent interaction capabilities with the microcontroller development ecosystem, this module can be made into several form factors and can be adapted to the needs it fulfills. This allows for the signal to be sent wirelessly and for processing tasks to be performed in a device that is computationally capable of real time accurate analysis. Newer and more modern hardware can take advantage of this approach and use it to their advantage for PPG based calculations. We present an integration of modular subsystems in an integrated device, such that every part is upgradeable, from the sensor to the microcontroller, and can furthermore use our algorithm to its advantage and to yield significantly more accurate readings. Improved and dedicated microcontroller units can also serve to perform more signal processing tasks from our algorithm before wirelessly sending the signal, allowing for an increase in sampling speed and the overall response time of our device, without affecting the increased accuracy reported in this work. A capable modern processor has the potential for increased complexity in the signal processing performed, allowing for our novel motion artifact tailoring algorithm to not only improve the quality of the signals obtained, but also expand the capabilities and uses of reflectance type,
portable pulse oximeters to a wider range of activities and environments.
Chapter 4. Multi-Wavelength and Multi-Signals

4.1 Introduction

A wearable pulse oximeter for continuous, real time monitoring was presented in the previous chapter. To further expand on the idea of removal of error, additional possible signals can be introduced to the device. These signals include more electrophysiological signals such as muscle and electrical signals from the brain. Additionally, adding channels to the existing PPG sensors in the form of different colored light will also benefit the overall results due to their varied interaction with different colored skin and penetration. This work was also performed was performed in collaboration with Dr. Hsiao-Chun Wu and Dr. Limeng Pu from the Electrical Engineering Dept. at LSU.

4.2 ECG and EMG

4.2.1 Data Collection

A system has been created, both software and hardware, in order to obtain EMG and ECG signals, process them through passive electronics and send them to a computer. Furthermore, signal processing is made on the program and the resulting waveform data is saved for further analysis. For EMG, surface electrodes are prone to various sources of noise. The voltage potential is obtained by calculating the difference between 2 electrodes (plus an additional reference electrode to eliminate constant noise), while reducing noise through passive filtering. Furthermore, the amplified signal is filtered with an active bandpass filter with more gain to better observe the signal. Surface EMG’s have a maximum amplitude of around 5mV, so the adjustable gain should be around the range of 3 orders of magnitude in order to yield an observable signal. Most microcontrollers only take a positive range of 0-5V, so the signal is adjusted accordingly. This is made by utilizing a rectifying diode layout. The current setup is adjusted for wireless
communication to the of power, ground, and both raw plus processed signal.

![Figure 4.1 Block Diagram of EMG Hardware](image)

ECG records the heart’s EP pattern of depolarization and repolarization occurring in each period (or heartbeat). A typical signal obtained from ECG electrodes contains many key components that can be obtained through signal processing. The main components, or peaks of interest, are the P, Q, R, Q, and T peaks. These specify intervals that yield interesting information about the heart’s functionality. In this case, ECG signals will be measured utilizing a compact system that will wirelessly transmit information to a capable device for processing and display purposes. While the compact system will utilize the simplest of ECG acquisition schemes (single channel), there are various signal features that can be extracted from such signal that can be proven
useful for a variety of applications, if filtered and analyzed properly. For example, the PR interval, is the initial trigger that causes contractions in the in the heart’s internal atriums, and specifies the initial wave that causes depolarization. The QT interval, as another example, is the more involved process that generates the heartbeat that we typically sense (highest peak). Within the QT interval, we can obtain other information such as the ST segment, which specifies the repolarization of the heart.

The system will obtain ECG signals, process them through passive electronics, digitized, and further sent wirelessly to another device. Furthermore, signal processing is made on the device in real time and the resulting waveform data is saved for further analysis. The overall steps done in the circuit for the obtained signal are shown below, in a similar manner to EMG. Surface signals have a maximum amplitude of around 5mV, so the adjustable gain should be around the range of 3 orders of magnitude in order to yield an observable signal. Most microcontrollers only take a positive range of 0-5V, so the signal is adjusted accordingly. The circuit design is presented below.

![Figure 4.3 Block Diagram of ECG Hardware](image)

Figure 4.3 Block Diagram of ECG Hardware
Figure 4.4 Circuit Design for ECG

The components mentioned can be observed below. Note that their footprints are considerably small and can be incorporated into a single, wearable sensor.

4.2.2 Analysis and Control

Once the signals have been received, a LabView Program was developed to analyze it and process it using the MA tailoring proposed [10]. The microcontroller receives the signal and converts it to digital, which in turn is sent to the computer running LabView. The LabView main program is shown below (figure 4.6) and the resulting front panel is shown in figure 4. The main task of this program is to obtain, filter, and represent the signal in a way that is easier to analyze in the future. Two different signals are obtained from the Arduino, the raw EP signal and the processed (rectified plus filtered) signal.

The signal processing is done mostly on the filtered signal. This signal contains the envelope of the raw signal, and can be used for amplitude thresholding in control systems. EMG signals are known to range from 10 to 1000 Hz in frequency, so a Butterworth filter is applied in these ranges...
to yield the desired output signal. The reading frequency used in this case is 80 samples per second, so we set the filter to 160 Hz sampling frequency to obtain a better filtered signal. In the front panel from figure 4, there are several controls that can be adjusted. The main controllable parameters are: the sources of signals (analog inputs in the Arduino), the low pass and high pass frequencies of the Butterworth filter, and finally the port to which the Arduino is connected to the computer. For amplitude analysis purposes, a green object was added that will light up when the signal exceeds a predetermined threshold. This threshold can be used for other applications such as control systems and stand-by power saving methods. The signals were obtained at 400Hz sampling frequency, which allowed for all signal components to be obtained. A sample obtained signal is shown below, clearly showing the main QRS peaks.

![Figure 4.5 Sample Raw ECG Signal Obtained](image)

Sample resulting signals are also shown in the front panel. For this figure, for example, 9 muscle contractions were performed and the resulting raw and processed signals were plotted in an amplitude (V) vs sample display. The raw signal will be utilized for frequency spectrum analysis to determine if there is any inherent differentiation between different movements of the muscles, relating to hands, fingers, wrist, etc. This, again, could yield a breakthrough in the control of prosthetic limbs for disabled subjects.
With more capabilities have been added to a robust system to read and analyze additional EP signals (EMG and ECG, in this case), several potential applications have been discussed to aid in error correction for comprehensive biometric sensors. For example, using amplitude to control motors has been proven. A wearable armband (figure 4.8) containing both the EMG sensor (Myoware) and the Arduino Nano board has been made to easily control motors and prosthetics with threshold voltage queues. In this case, the Arduino itself is performing the image processing with the same parameters, and the LabView Program is not used. This is because the role of the LabView program is mostly for signal analysis and representation. Since we do not necessarily
need these functions, plus the fact that the system should be fully wearable, the Arduino is the only processor required. Successful control of motors has been achieved with high reliability using a single and multiple EP sensor.

![Image 1](image1.png)  
**Figure 4.7 Wearable EMG and ECG System**

Measurement and analysis of EMG signals has been achieved without the need of large and expensive medical tools. With the help of existing hardware plus custom software, a clear and high SNR signal has been read. Further analysis and processing on such signals is now easier and more convenient. A wearable EMG system was also made that can be worn at all times using an armband interface and can be utilized for control purposes.
Successful measurement and analysis of ECG signals has also been achieved without the need of large and expensive medical tools. With the help of existing hardware plus custom software, a signal has been read and sent wirelessly to a capable computer. Further analysis and processing on such signals is now easier and more convenient. A wearable ECG system was also made that can be worn at all times using an armband interface and can be utilized for control purposes.

Further signal analysis and correlation with PPG is the main potential of this system, allowing for capable devices to implement complex signal processing on the ECG waveforms and extract all features of interest. As mentioned before, motion artifacts can be an issue for reading clear signal.

4.3 Multi-Wavelength Error Correction

Since the human skin is a layered structure containing various vessels at different depths, these can be probed using specific colored light illumination. Several studies have determined which wavelengths are optimal for scattering at these different layers, such as epidermis, dermis, and hypodermis [3-5]. Research on PPG signals in turn involves measuring changes in blood volume at different depths. For example, blue and light can probe capillary changes, while red and NIR can measure arterial. Other information studied will include heartbeat, timing, and other indicators that can lead to additional diagnoses on subjects.

These sensors will also address some of the most prominent issues currently present with typical PPG measurement systems. Mainly, noise through pigmentation can greatly affect the quality of the signal obtained, thus reducing accuracy and reliability of these types of sensors. The implemented devices are able to address these issues through wavelength switching by utilizing the sensors themselves as a feedback system to determine the optimal wavelength and current for every subject.
In this work, I developed a wrist-worn device to capture PPG data from several light sources (see figure 1 below) using a reflectance-based probe. This is able to obtain all colored signals simultaneously, and continuously monitor what is being reflected from the skin (see figure 4.9 and figure 4.11) Furthermore, it varies the light and surface colors, as well as adding artificial motion artifacts (rubbing, sliding) to introduce error conditions to the system. Results have demonstrated the effectiveness of our previously proposed motion artifact removal system.

To address the issue of light penetration, a multi-wavelength setup for skin illumination is proposed, with the addition of other signals such as ECG.
Figure 4.9 Skin layers and LED penetration through different layers [3]. In reflectance mode, the light emitter and detector are placed on the surface of the skin, and different colored lights (IR and Red in this case) will reach different sub-layers of the skin.

Figure 4.9 above demonstrates a common reflectance-type setup to obtain PPG using two different colored lights (blue and red). At different depths, the observed volume changes might be caused by different stages of blood circulation throughout the body. In particular, various layers of arteries, arterioles and capillaries exist for a given illumination site. Flood flow will flow through them in the same sequential order, meaning that volume changes will occur at different (but predictable) times. Higher wavelength lights such as red or IR are commonly used for PPG due to their higher penetration on the skin. This means that deeper artery signals will be possible to be measured. Noise in this case, however, is introduced through light interactions in light interaction due to layers and arteries closer to the surface than the intended target. On the other hand, shorter wavelength light is able to capture more shallow signals, but might be degraded by skin color when changing from layer to layer. As observed, a single colored light can be problematic, as varying depth penetration might rotate between different layers of the skin, compromising the reliability of the signal observed. A feedback system will be able to choose the colored light that gives the most reliable data for the current user. In particular, darker skin, or a lighter environmental illumination will yield the use of the IR signal for authentication, while lighter skin in a darker setup will use the GREEN signal. Current changes will also be implemented in order to adjust the overall amplitude of the reflected or transmitted light, as a function of skin
pigmentation and external illumination.

Figure 4.10 PPG waveforms from different colored lights in a transmittance-mode setup, in comparison with heart activity (from ECG) and pulse activity from blood pressure monitor [24].

Different colored measurements are also evaluated in terms of their autocorrelation and how additional features can be extracted from each. These findings can yield additional potential applications and more robustness in existing ones such as our authentication algorithm, since more features can be introduced to identify individuals. As seen in figure 4.11 above, and as previously mentioned, blood flow through different veins occurs at different times, so the colored signals will show peaks and valleys at different times. This time difference between signals will also be further studied to identify its significance with the overall physiological data we wish to identify.

Finally, to address the issue of the baseline drift and the motion artifact, it is necessary to implement an extended Kalman filter and improve our MA algorithm on each signal. Kalman filters are widely used robotics and time-series analysis such as signal processing and economics [32]. The extended Kalman filter is the nonlinear version of the Kalman filter [33]. In general, the baseline drift is observed as the DC component in the signal. Thus, the extended Kalman filter can be implemented to estimate the current state of the signal in a time slot, which will estimate the baseline in the corresponding time slot. By removing the baseline component from the signal, drift is minimized. For motion artifacts, one can use existing data from shallow signals (i.e. blue or
green) to tailor and remove unwanted peaks from deeper signals (i.e. red or IR). This will improve the performance of the MA tailoring algorithm, further increasing the accuracy of our overall system, and most importantly, decreasing the time window required to identify a person. This will further decrease the speed of our algorithm and signal acquisition time.

4.4 Conclusions

For the additional signals discussed above, an increase in reliability and robustness of a true wearable biomedical system has been achieved. The proposed motion artifact tailoring algorithm can greatly increase the accuracy of not one but multiple wavelengths of reflected/transmitted light throughout the skin. This allows for flexibility among conditions out of the sensor’s control, such as who is wearing the device and what external lighting or motion there is.

Furthermore, other EP signals also affected by motion noise can also be tailored and used in conjunction with PPG and among themselves to acquire more information and make more conclusions about the subject.
Figure 4.11 Sample waveforms with pigmentation. (a) normal surface; (b) wet surface; (c) black pigmented surface; (d) green pigmented surface; (e) red pigmented surface; (f) white pigmented surface; (g) green taped surface; (h) purple taped surface
Chapter 5. Sensor Networks in Real Time

It has been demonstrated how multiple sensors can work together to address common sources of error in a specific application. To further expand on this idea, additional fields that are greatly dependent on false negatives and positives are explored. Since non-invasive and light-based sensing platforms are of additional interest, a network of distance and environmental sensors is initially presented to create real time and high-speed vehicle profiling to prevent major accidents in everyday traffic. This work was developed in collaboration with the Civil Engineering Department at LSU under Dr. Aly M. Aly and Dr. George Z. Voyiadjis, and the Louisiana transportation research center (LTRC).

In addition, full environmental profiling and logging will be performed for both reporting and error correcting for this purpose.

Additionally, another fully deployable environmental sensor network will be set in a compact, wearable device to characterize noise profiles in construction sites and process recoded data in real time. This data is not limited to the aforementioned environmental parameters, but also to noise and differential noise pressure from highly sensitive microphones. In this case, a cloud-based platform will be used to capture and log all received data in real time for further analysis.

5.1 Highway Sensor Network

This work shows an overheight vehicle detection system (OVDS) using both laser and ultrasonic sensors with wireless LTE and RF communication to an off-site central command and a warning signal, respectively. We focus on the main purposes of such system, height detection and warning, while addressing the most common issues observed in installed systems. The majority of these issues are error correction, false positives, power, cost, and speed. A full implementation and installation of such system is shown, with the ability to monitor and profile
moving vehicles to determine if they are overheight, and further warning them to act. This is implemented in two different lanes, with the capability of expansion in the future.

5.1.1 Design Overview

The overall functionality of the system is shown in Figure 5.1, where continuous communication between the sensor system and both a warning signal and a control command is crucial for detection, logging, and warning of an overheight vehicle. The proposed system is divided into two subsystems. The first one will determine whether the incoming vehicle is clear to pass, depending on its height. This can be accomplished with several different methods. One option relies on distance sensors placed directly above the street (either under a crossing bridge or under a sign). These sensors would detect the exact height of each passing vehicle. A second option can utilize an array of laser sensors placed on both sides of the road at specific heights. This would basically allow the detection of the highest point of a vehicle and indicate whether or not it can pass. For the overheight decision making in our system, we use not one but a combination of both vertical and horizontal sensors to determine if a vehicle is clear to pass an upcoming obstacle. This decision-making process is described in Figure 2 and will be further detailed in the next section.

The second subsystem acts in reaction to what the first has determined about a vehicle. This system consists of an indicator to the driver about their vehicle not being able to pass and to take the nearest bypass road. Once a vehicle is determined to be outside the accepted height threshold, this second subsystem will also log and send data about the event locally, including images, date, time, and height information. Furthermore, it will use cellular data (via a subscriber identification module or SIM card or mobile hotspot) to communicate with the central command and send it the required and pre-determined information.
Figure 5.1 Overall system functionality of the proposed system, describing an overall simplified workflow of a constant loop for detecting whether a vehicle exceeds a height threshold, and how the system will react to such case.

Figure 5.2 Detection and non-detection decision making for the proposed system using vertical and horizontal sensor data.

The main objective of the height profiling system is to determine the height of an incoming vehicle. For this purpose, different distance sensors exist that satisfy the required specifications. Laser sensors consist of an emitter that will send a pulse of laser light and measure the reflected
pulse as it returns to a receiver. The time difference between these two events is measured with high precision and converted to a distance measurement. These beams travel at the speed of light, yielding high rate of reading to detect fast moving objects. Laser sensors are usually more expensive and work for ranges up to 200 m (or 650 ft). State-of-the-art laser sensors can reach a signal obtaining rate of up to 1,000 samples per second. Each laser-based sensor can consume up to 100 mA of current with a 5 V voltage supply, with operating temperatures of up to 85°C (or 185°F). A typical laser sensor would then consume around 500 mW per each sensor, on average. On the other hand, ultrasonic sensors work on similar principles. The difference is that high frequencies are sent instead of light beams and reflections are measured. These sensors have lower costs but can reach distances up to 20 m (or 65 ft), on average. Sound waves, however, travel slower and are more prone to inaccurate measures due to additional noise and a lower intensity signal (light is easier to focus than sound). However, ultrasonic sensors can compensate possible errors of laser sensors during heavy rain or dense fog conditions. Ultrasonic sensors can reach a signal of up to 500 samples per second. Each ultrasonic based sensor can consume up to 25 mA of current with a 3.3 V voltage supply, with operating temperatures of up to 65°C (or 150°F). A typical ultrasonic sensor consumes around 12.5 mW per each sensor, on average.

These time-of-flight (ToF) sensors are a viable option due to high read rate (around 1,000 Hz) and acceptable power consumption of around 600 mW per each sensor, on average. These sensors also utilize laser-based transmitters and can work at long ranges of up to 40 m (or 130 ft) with minimal crosstalk.

For this reason, there has been extensive use for these types of sensors in situations where high-speed detection is required, such as obstacle and collision avoidance or high-speed autonomous navigation [41-43]. This purpose satisfies the needs of our system, since high speed
vehicles need to be profiled in an accurate way.

The combination placement of these sensors to achieve the objective involves placing laser sensors on both sides of the road, and on top of the lanes. This hybrid lateral/vertical arrangement of sensors has the advantages of lateral and vertical sensors in one system.

This system utilizes a vertical setup with overhead sensors to determine the height of a vehicle. These sensors can be placed either under an intersecting bridge or already existing structure, or on a specifically built structure. The sensors placed have to be fast enough to detect every passing vehicle at high speeds. Infrared lasers and ultrasonic sensors can both measure under the required conditions.

Horizontal sensors, although also laser-based, do not measure the distance from emitter to the vehicle for height, but to determine the presence of such and in which lane it is located using distance windows. These will further aid in error correction and false positive prevention. Based on distance thresholds on each, the sensing systems will determine if 1) a vehicle is actually present at the time of detection, and 2) the vehicle’s height profile and if it exceeds a height threshold. This will directly aim to remove the false positive issues aforementioned. This will directly aim to remove the false positive issues aforementioned that can occur from external sources of noise (i.e. passing animals, weather, etc.) that might trigger a high vehicle warning if not accounted for. A simple decision schema is shown in Figure 5.2, where a detection will only be logged if both presence and height threshold occur within the same time frame.
Figure 5.3 OH detection and warning algorithm for x lanes. Individual setups can be installed per lane, with horizontal measurements determining presence of a vehicle and specific lane in which it is detected.

A considerable distance between the sensor and the warning sign must be used in the system for the driver to have enough time to see and react to the warning telling them to take the nearest bypass exit. Cellular data is used to communicate with the central command for data logging purposes. This data transmission consists of reports, pictures, and time logging of events where an overheight vehicle was detected. Radio frequency (RF) is used to trigger the warning sign about 500 ft away from the sensors. The transmitter side (sensor sign) can send an analog signal (single frequency tone) to the receiver end. The receiver end will interpret that signal as a height threshold violation and will promptly activate the warning.

5.1.2 Implementation

Our demonstration OVDS was implemented in street in our city for the detection of overheight vehicles on two separate lanes. A flow chart of our detection algorithm for two lanes, in a continuous loop and as seen in Figure 5.3, summarizes how our system was implemented to address the issues with false detection. All sensors are active at all times, including a camera for real-time monitoring. Initially, horizontal sensor values (lateral laser sensors) are collected and averaged to determine lane. This includes filtering and averaging to avoid noise. This value is first
compared to a presence threshold, which indicates if there is a vehicle present in any of the two lanes being observed. If this is the case, the averaged value is evaluated to predetermined ranges of distance thresholds and used to determine in which lane the vehicle is present. In this case, and since two lanes were used, the midpoint between the lanes was used as a determining threshold.

![Installation of vertical sensors (top) and sample weatherproof enclosure for sensors (bottom) for the proposed OVDS.](image)

When a lane is determined, vertical sensor data (overhead sensors) will be used to calculate an average sensor-to-vehicle distance. This is then subtracted to the calibration measurement (which is the sensor-to-ground distance) to calculate average vehicle height.

Once this data has been collected, we determine if the vehicle height exceeds a previously determined threshold, meaning that the vehicle is too high. If this is the case, height data, along with vertical data and date/time are logged, and the warning signal pin will be activated. This also triggers camera frames at that moment in time to be stored in order to capture an image of the vehicle being profiled. All sensor data for vehicles exceeding the threshold, along with time-
stamped images, are appended to a report that will be sent periodically or obtained on-demand through a remote connection.

Table 5.1 Distance Sensors used in OVDS

<table>
<thead>
<tr>
<th></th>
<th>Vertical Sensors</th>
<th>Horizontal Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
<td>Teraranger One [45]</td>
<td>Lidar Lite [44]</td>
</tr>
<tr>
<td><strong>Principle</strong></td>
<td>Infrared Time-of-Flight (ToF)</td>
<td>IR Laser Time-of-Flight (ToF)</td>
</tr>
<tr>
<td><strong>Dimensions</strong></td>
<td>35 mm x 29 mm x 18 mm</td>
<td>20 mm x 48 mm x 40 mm</td>
</tr>
<tr>
<td><strong>Field of view</strong></td>
<td>3 degrees</td>
<td>0.5 degrees</td>
</tr>
<tr>
<td><strong>Supply voltage</strong></td>
<td>12 VDC</td>
<td>5 VDC</td>
</tr>
<tr>
<td><strong>Supply current</strong></td>
<td>50 mA average</td>
<td>135 mA average</td>
</tr>
<tr>
<td><strong>Connector</strong></td>
<td>15 pin DF13</td>
<td>8-pin connector</td>
</tr>
<tr>
<td><strong>Weight</strong></td>
<td>8 g</td>
<td>22 g</td>
</tr>
</tbody>
</table>

The components utilized for the sensing system are described in Table II. Note that repeated sensors are used throughout in order to achieve redundancy and further increase the accuracy of the system. For vertical sensors, Teraranger One (Terabee, SAS) were used for height determination with a sensor HUB (Teraranger Hub, Terabee, SAS) used to manage power and serial data. For horizontal sensors, Lidar Lite V3 laser time of flight rangefinders were used (Garmin, Inc). Note that repeated sensors are used throughout in order to achieve redundancy and further increase the accuracy of the system. Furthermore, a Raspberry Pi 3B single board computer (Raspberry Pi Foundation) is utilized as the on-site computer for data management, and a Sierra RV50 (Sierra, Inc) modem is utilized to transmit LTE data. Additional components include simple RF transmitter/receiver pairs, as well as a USB Webcam (Logitech, Inc) for image capture. All of the individual components and subsystems are enclosed in NEMA 4X rated metallic enclosures to assure weather and environmental condition proofing.
5.1.3 Installation

Full installation was completed for all components on the demonstration site. These included weatherproof enclosures with appropriate windows and conduit wiring for all sensors to interact with the main computer. The first set of components were 3 overheight sensors with the Teraranger distance sensors and top camera (Figure 5.4). These were further installed on the back of traffic signals to protect from wind and prevent obstruction on the lights themselves. An additional enclosure was included, with the sensor hub for vertical sensors, the camera, and an additional vertical sensor for one of the lanes. Horizontal components were installed on both posts on opposite sides of the road, facing the road at different sides to detect presence and height thresholds. On the same and opposite posts, the loggers and power management were installed in order to collect all data, process, and send it appropriately for decision making and logging. Camera feed is also processed at these loggers. Additionally, solar panels and power converters were installed on each logger in order to deliver power to the sensors and the modem used for wireless transmission, satisfying all power requirements for continuous functionality.

5.1.4 Overheight Monitoring Results

All sensors were calibrated and characterized using known values of distance to street (ground with no car) and distance between poles. These were further compared with thresholds to divide lanes (lanes 1 and 2 in this case) and height/presence. We used the decision-making algorithm depicted in Figure 2 for two lanes, where they are demonstrated to work using all installed components aforementioned. Further calibrations and performance results were performed using empty streets and known values, including lane width, street dimensions, distances between poles and distance between sensors. These were also accounted for with variations in environment, field of view, and temperature surrounding each sensor.
For monitoring, a remote VNC client was installed in the loggers. This was implemented to access all data, images, and reports remotely from anywhere with an internet connection. This also allowed for troubleshooting and code modifications without visiting the installation site. An overview of the user interface is observed in Figure 5, showing all raw data through a serial port and images as obtained continuously when the system is running.

All sensors are active at all times, including the camera for real-time monitoring. Initially, horizontal sensor values are collected and averaged to determine lane. This includes filtering and averaging to avoid noise. This value is first compared to a presence threshold, which indicated if there is a vehicle present in any of the two lanes being observed. If this is the case, the averaged value is evaluated to the midpoint between the two lanes (is the value higher or lower?) and used to determine in which lane the vehicle is present.

When a lane is determined, vertical sensor data will be used to calculate an average sensor-to-vehicle distance. This is then subtracted to the calibration measurement (which is the sensor-to-ground distance) to calculate average vehicle height. Figure 5.5 shows an example of the data collected from a vertical and horizontal sensor within a small period of time. The vertical data represents the time of flight time sensing from each distance sensor, in milliseconds, and used to
calculate the vehicle height. The horizontal data, on the other hand, is also a time of flight measurement which is used for the purpose of determining if a vehicle is present and in which lane. Both sensors have been normalized to zero in order to account for outlying data.

Once this data has been collected, we determine if the vehicle height exceeds a previously determined threshold, meaning that the vehicle is too high. If this is the case, height data, along with vertical data and date/time are logged, and the warning signal pin will be activated. This also triggers 6 camera frames to be stored in order to capture an image of the vehicle being profiled. All sensor data for vehicles exceeding the threshold, along with time-stamped images, are appended to a report that will be sent periodically or obtained on-demand.

For each incident, height is calculated based on the average distance from the vehicle to the sensor, when compared to the distance between the sensor and the ground. This value is further used to categorize each vehicle based on its class. These classes include compact, mini SUV, large SUV, and truck. With additional calibration and noise reduction, the system will be able to accurately show height of each vehicle as it passes its threshold. Sample resulting picture and measured height can be observed in Figure 5.6, with the clearest of the 6 frames taken saved. These samples include the time index used to calculate the time of day, as well as the resulting height and category of the vehicle. From the data shown in Figure 5.6, vertical and horizontal peaks determine both the height and presence of a vehicle at a given time. The horizontal data, measures in milliseconds, determines not only the presence of a vehicle in the sensor’s line of sight, but also in which lane it is detected. Higher peaks translate to further lane intersections, with no detections normalized to 0. On the other hand, vertical data will be measured by the calibration value in milliseconds minus the detected time of flight to a vehicle. This will result in a time of flight measurement directly related to the vehicle’s height.
With an arbitrary threshold set at 2000 ms, the vertical alarm was triggered in the red regions observed above. A detection is logged if and only if both peaks are triggered at the same time, as described in Figure 2, resulting in the two different instances aforementioned. If only one is detected, however, the system considers it as noise and no detection will be logged or reported.

Other highlights to note include the collection of data based on distance to sensor thresholds, upon which the algorithm will log the time/date of the data point and store its corresponding picture. Normalization of pictures being taken is implemented to save storage space on the on-site computer, meaning that the camera will only take 6 pictures when a presence
threshold is activated, as mentioned before.

Addition of anti-crosstalk code was due to repeated sensors placed for each lane or level and enabled the command for the sensors which activates them one by one. There exists negligible delay in signal acquisition so it should not affect the system functionality. Sample resulting images and data were locally stored in the on-site computer to be sent in periodic reports via email, text message, or other ways of communication using the LTE connection.

5.2 Sound and Environment Sensor Network

5.2.1 Summary of Work

In collaboration with the Department of Civil Engineering at LSU, we have developed a sensor network system to provide an on-site solution for capturing and categorizing sound parameters within a construction site. In addition, other measurements were also included such as temperature, geolocation, humidity, and pressure. This was accomplished in a low power, small footprint, and completely wireless sensor hub that constantly uploads required data to an online server for machine learning and further processing. Several solutions were proposed for this system, with a wearable unit serving as the main data collector and off-site signal processing using cloud services or a centralized computing unit. Within the context of this dissertation, we aim to use such parameters within a network of sensors for real-time monitoring and off-board signal processing. Furthermore, increased number of sensors in a deployable system allows for higher accuracy through redundancy and error correction.

5.2.2 Project Overview

For various iterations and prototypes, a low power microcontroller unit (MCU) or single board computer (SBC) were used, depending on the prototype computational needs. Each were interfacing with an environmental sensor array and a sound sensor array through a custom board
to monitor the aforementioned parameters. With a Wi-Fi-enabled system, these devices constantly stream data and periodically send audio files to an online cloud database, with period and sampling rate adjustable by the user. On-board processing includes calculating raw and average noise, temperature, humidity, altitude, relative pressure, and differential noise. The latter is possible due to a dual microphone setup used in all prototypes.

To complete the system, geolocation reporting and calculating is achieved using an additional GPS antenna or using a geolocation service with the included WIFI card. Three prototypes were developed with close to full functionality as described in the primary objective. Each were made as an improvement upon its previous one, with a focus on completing a fully deployable and independent system.

5.2.3 Initial Prototype

The initial package was packaged in a (88mm x 55mm x 30mm) custom case, along with two extruding microphones and an environmental sensor. It also has space for a rechargeable lithium battery and a micro-USB connection for power or reprogramming. All the individual components are described in detail below.

A NodeMCU ESP32-S microcontroller is utilized to capture and process all aforementioned data. Furthermore, it is connected to our established cloud account and constantly streaming all required data as periodic messages. For testing purposes, it also prints all measurements to a serial port for on-site troubleshooting. The device can be reprogrammable with Arduino IDE through a USB connection, and is powered in a similar manner.

Dual MEMS microphones (labelled right and left) are installed and communicate to the MCU through I2S protocol. This is because the microphones send a digital signal to the board, instead of an analog noise signal. This will further save time and computer resources, as no analog
to digital conversion is required prior to sending data. It is important to have dual microphones in order to calculate additional parameters from noise, including average and differential noise pressure.

A simple environmental sensor has been installed at the bottom of the case, based on an BME280 temperature, barometric altitude, and humidity sensor. It communicates with the MCU with I2C protocol, sending updated data at a high frequency, as required. The current system is capable of capturing all data and sending to a Microsoft Azure IOT Hub through a standard JSON formatted message. Furthermore, the cloud server has been programmed to import the message and translate it to a processing data array to be stored in its SQL database for further analysis. A sample of sent data and received SQL ready array can be seen below, seeing how headers and labels are translated into a table format dataset.

![Figure 5.7 Raw data in JSON format (left) and received data in cloud server (right). Data is automatically organized and categorized in the server.](image)

All of this information is being calculated in real time and streamed wirelessly to be accessed from any site. We have set it to a 5 second period for testing, but can reduce the time between messages at the user’s discretion.
5.2.4 Finalized Working Prototype and Final Design

The limitations of the initial MCU included no on-board storage and no dedicated GPS antenna. Furthermore, we are only able to change or modify the code using a wired USB connection with a computer. The next iteration developed included additional key features and improvements. These optimizations were focused on the implementation of on-board storage to store audio clips and other data to be sent over time, complete remote access to a desktop environment on the board in order to modify code and fetch any on-board data for troubleshooting, and a dedicated GPS antenna for greatly increased accuracy of geolocation. For this purpose, a Raspberry Pi 3B+ (Raspberry Pi foundation) was used. This is a more capable Linux-based single board computer with a desktop environment that allowed for a custom program to be implemented.

The system, pictured below, interfaced with the same dual microphone setup (figure 5.8)
and a minimized environmental sensor through a connection board to power and control each device independently. Furthermore, it has an external GPS antenna to capture location and elevation data in real time to send and report accordingly (figure 5.10). The GPS antenna board also includes an accelerometer for additional environmental parameters to be reported, if necessary.

![Figure 5.10 Sensor Interface board and SBC](image1)

![Figure 5.11 Final GPS Breakout board (left) and environmental sensor board (right)](image2)

This second prototype design addressed all computing and interfacing needs for a final design. The finalized design overview can be observed in the figure below and was used by all prototypes developed, with all aforementioned components included within a single wearable enclosure. The same components were utilized as before; however, with an optimized data
collection algorithm, a smaller SBC was used to collect all data. In this case, a Raspberry Pi Zero W (Raspberry Pi Foundation) was used within an enclosure. This device also had the same sensors, GPS, and microphones, but utilized a smaller footprint due to both its smaller form factor and the interface board to connect all peripherals. Furthermore, battery size and removal of USB connections for modules also contributed to the miniaturization of such device.

Figure 5.12 Final design for the deployable environmental sensing system
Chapter 6. Conclusions and Summary of Work

6.1 Summary

In this work, the impact and advancements in sensing systems have been presented, with a focus on wearable and non-invasive devices, errors and challenges have also been introduced, presenting an opportunity for improvement using both novel algorithms in software, or implementation of additional channels working in conjunction to address conflicting noise. This will allow for more robust and deployable sensing platforms for a wide variety of applications in commercial and industrial fields.

Initial chapters focus on the use of sensor platforms for biomedical and wearable sensors. In latter sections, the idea of multiple sensor systems is expanded upon other applications. Such applications include vehicle profiling in highways, and ambient sensor networks. With such abundance of data, solutions to properly analyze them are presented through the use of cloud computing and signal processing. Multi-signal processes to address errors and noise are further presented, such as redundancy and constant calibration, to further increase accuracy and create reliable sensor networks. Power solutions are also discussed with a focus on conservation and harvesting of energy.

6.2 Signal Integration and Decision-making

The use of visible light and other contact methods has no adverse effect on the surface of the skin and is ideal for non-invasive monitoring of the user. These signals, however, have been largely unexplored for additional applications, and I expect my research to bring new light to the possibilities of multi-wavelength PPG and multi-signals in the future. There is a great need to explore different aspects of colored PPG waveforms in order to find correlations amongst themselves and with additional biometrics (i.e. ECG, breath rate, etc.), which might serve as
indicators to diagnose or monitor physical conditions for health or personal wellness in real time. Furthermore, the robustness and continuous accuracy of a fully developed system will open this device to additional applications both inside and outside the field of health. As mentioned before, these can include applications such as security, user profile determination, battery life management, and custom user settings for a device, among many others. And PPG signals have tremendous advantages over the other biometrics in use for non-medical applications. Additional expected work and experimentation can be defined in different actions. First, it is always necessary to improve the overall signal quality and remove baseline drift of all signals. This can be done from the preprocessing perspective by using Kalman filter to adaptively mitigate the baseline drift. Further investigation the effect of motion artifact under different surface conditions. Existing hardware will be further optimized to utilize the light detector not only as a signal acquisition unit but also as feedback system to adjust the LED currents. The system will be able to turn LEDs on or off, as well as fine tune their intensities using current changes. This will also adapt to different skin pigmentation to acquire the best resulting waveform based on a specific color. Modify existing software to use the feedback from the light detector in order to adjust current and wavelength desired for a specific environment. I will do this by studying the effects of the aforementioned LED changes with different pigmentations and environmental conditions. Final analysis and evaluation of correlations between light colors, as well as between other physiological factors (i.e. heartbeat, oxygenation, breath rate) and how these can lead to additional features used for authentication or other applications is always desired throughout the process.

6.3 Power Consumption optimization

While most wearable and visible light sensors used in this work are relatively low power. It is
highly desired to optimize power consumption as much as possible for a deployable system. This is because continuous and real time monitoring are crucial in the applications mentioned throughout this work. Optimization of power can be represented in both evaluating when each sensor should be active and when data should be collected and transmitted. Furthermore, additional sources of power can be introduced in the form of power harvesting. Obtaining supplemental power from motion or the environment inherent to the system’s surrounding can prove beneficial to optimize battery life and increase the independence of each system. For this purpose, power harvesting from sunlight and triboelectric (contact electrification) methods will be implemented in all devices to collect data, tailor noise, analyze, and finally report.

6.4 Basis for Future Work

This paper presented the basis for deployable and independent sensor networks with true error correction and prevention. However, there is always room for improvement on aforementioned challenges for all systems. Future work can be performed not only on power management like mentioned in the previous section, but also on how sensors interact between themselves and with the data collecting system. A feedback loop inside such systems can be expanded upon for sensors to constantly adapt to their surroundings, yielding the highest accuracy possible for the given time.
References


Vita

Pedro Chacon was born in Tegucigalpa, Honduras on Christmas day in 1990. He graduated from Macris School in the same city in 2009. Upon graduation, he moved to Houston, Texas, USA to complete his undergraduate studies. He received a Bachelor of Science in Electrical Engineering at Rice University in Houston, TX in 2013. After a year of industry work in Racine, Wisconsin, USA, he began pursuing his doctoral and master’s program at Louisiana State University in Baton Rouge, Louisiana. He is expected to graduate in the summer of 2021 from the Electrical Engineering doctoral program. His current research interest includes error correction noise reduction, and power optimization in sensors and sensor networks, wearable sensor systems, non-invasive electrophysiological sensors for continuous use.

List of Publications


