Processing Motion Artifacts for Improved Non-invasive Blood Oxygen Level Estimation

Bishmoy Paul
1706109@eee.buet.ac.bd

Md. Nafis Washir
1706129@eee.buet.ac.bd

Shahriar Ahmed
1706135@eee.buet.ac.bd

Fariha Ferdousi Khan
1706143@eee.buet.ac.bd

Fatin Fardaous
1706160@eee.buet.ac.bd

Shariyar Kabir
1706184@eee.buet.ac.bd

***Abstract*—This project presents an approach for processing motion artifacts in non-invasive blood oxygen level estimation. Motion artifacts can severely degrade the accuracy and reliability of pulse oximetry measurements, which are commonly used to estimate blood oxygen levels. Our project combines adaptive filtering techniques with motion data to reduce the impact of motion artifacts from pulse oximetry signals. We demonstrated the effectiveness of our approach in real-time data and showed improvements in blood oxygen level estimation accuracy compared to the baseline method used to estimate it. Commercially available pulse oximeters are used as the gold standard to estimate the effectiveness of the project. Our project has the potential to improve the reliability and utility of non-invasive blood oxygen level estimation in a wide range of healthcare applications.**

***Index Terms*—Pulse Oximetry, Photoplethysmograph, Motion Artifacts, Adaptive Filtering**

I. Introduction

Measuring blood oxygen level has become a useful way of identifying the severity of COVID-19 or other lung diseases such as Pneumonia. Timely recognition of lung problems and seeking the proper medical help can be of paramount importance in saving the patient's life. Testing blood for measuring oxygen level is an invasive procedure that is difficult to perform without the help of experts. Non-invasive methods, though widely available, cannot produce results as accurately as invasive methods, and hence improving the performance of non-invasive methods can be very useful from a medical standpoint.

Motion artifacts are a common problem in non-invasive diagnosis methods. In biomedical signals, motion artifacts can occur due to the movement of the body or the limbs, breathing, or other physiological processes. Motion artifacts can cause significant distortion in the signal, resulting in inaccurate or unreliable measurements. In particular, motion artifacts can severely degrade the accuracy of physiological measurements such as pulse oximetry signals.

In our project, we have developed an improved noninvasive blood oxygen level estimator utilizing commercially available sensors and microprocessors based on photoplethysmography (PPG). As PPG sensors are often affected by motion artifacts, we processed the photoplethysmographic signals utilizing aclerometer sensor information to improve the accuracy of the readings and reduce errors.

TABLE I
COST TABLE

#	Component	Cost (BDT)
1	Arduino Uno R3	955
2	Heartbeat Sensor Module	872
3	3-Axis Accelerometer	701
4	Jumper Wire Set	157
	Total	2,685

II. Methodology

For our project, we used a PPG Sensor on the patient's skin and send the data to the microcontroller. To get an estimation of the movement of the sensor, an accelerometer is also used to get data. The microcontroller would take the sensory data and process it to improve the sensor estimate of blood oxygen level. The output would be shown in a display connected to the microcontroller For a realistic baseline, a commercial pulse oximeter would be used to compare the output. An overview of the process is shown in II.

A. PPG Sensor

Each optical pulse oximeter and heart rate sensor, including the MAX30100, is made up of a photodetector and a pair of high-intensity LEDs (RED and IR, which have distinct wavelengths). These LEDs have wavelengths of 660 nm and 880 nm, respectively.

The MAX30100 operates by shining both lights onto a finger or earlobe (or where the skin isn't too thick, allowing both lights to readily penetrate the tissue) and detecting the amount of light reflected using a photodetector. Photoplethysmogram is the name of this technique for light-based pulse detection [2], which is shown in the Fig-II-A.

The foundation of pulse oximetry is the idea that the amount of RED and IR light that is absorbed fluctuates according to the level of oxygen in the blood. Red light (660 nm) is more readily absorbed by deoxygenated blood than oxygenated blood is by IR light (880nm). by calculating the photodetector's IR/RED light reception ratio. We can calculate the SpO2 index from a predetermined mapping of the reception ratio to predetermined oxygen saturation level.

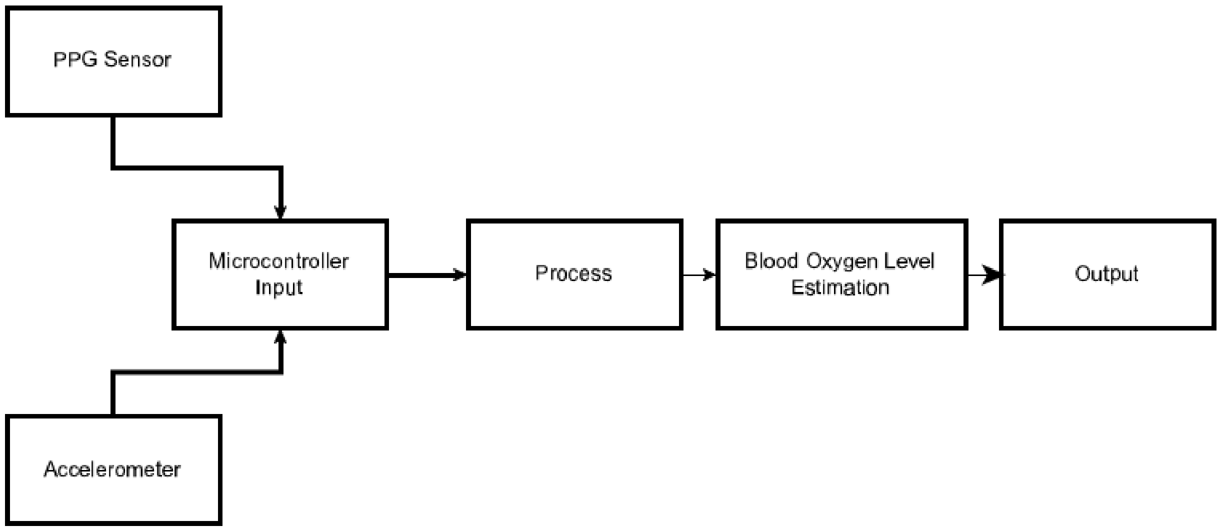

Fig. 1. Overview of the project

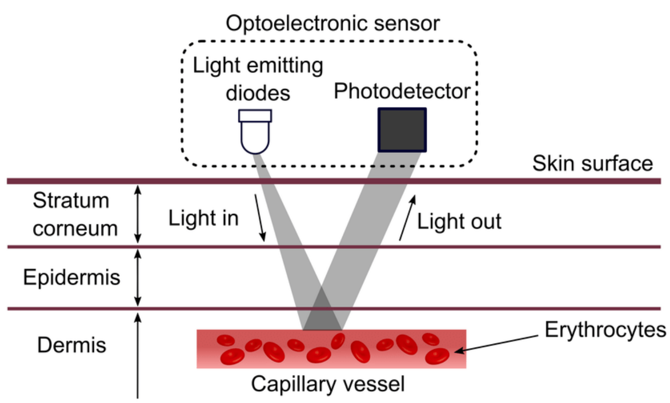

Fig. 2. Overview of PPG Sensor [1]

B. Accelerometer

The MPU6050 sensor is a compact and highly integrated module that combines both an accelerometer and a gyroscope, providing six degrees of freedom (6DOF) motion tracking. The accelerometer measures the linear acceleration of the device in three axes (X, Y, and Z), while the gyroscope measures the angular velocity around those same axes.

The MPU6050 sensor is based on Micro-Electro-Mechanical Systems (MEMS) technology, which uses miniature mechanical structures fabricated on a silicon chip to detect motion. It features a low power consumption and a high sensitivity, with a programmable full-scale range for both the accelerometer and the gyroscope.

C. Filter

The Butterworth filter is a type of infinite impulse response (IIR) filter, meaning that it has feedback in its design. The transfer function of the filter is characterized by a maximally flat magnitude response in the passband, meaning that it has a uniform gain across the frequency range of interest.

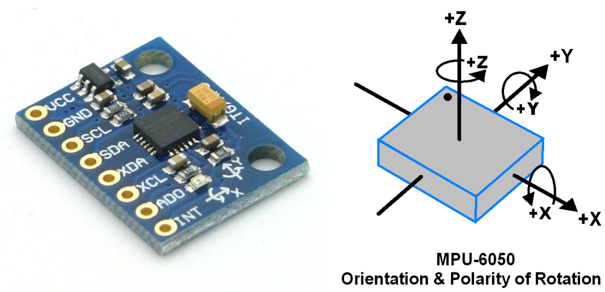

Fig. 3. MPU6050 Sensor

For our project, we examined the effects of time domain characteristics of the filtered signal both with and without motion artifacts using different filters. Finally, a low pass filter with a cut-off at 4 Hz is picked as the optimum filter for processing unnecessary noise in the data. The effects of the filter on both data with and without motion noise is demonstrated in Fig-II-C.

D. LMS Filter

The Least Mean Squares (LMS) algorithm is a type of adaptive filter commonly used in signal-processing applications. The algorithm works by iteratively adjusting the filter coefficients to minimize the error between the filter output and the desired signal. [3]

$$w(n+1) = w(n) + 2\mu e(n)x(n) \tag{1}$$

Where $w(n)$ is the vector of filter coefficients at time step n, $x(n)$ is the input signal at time step n, $e(n)$ is the error signal at time step n (difference between the filter output and desired signal) and μ is the step size parameter, controlling the rate of convergence. The error signal $e(n)$ is given by:

$$e(n) = d(n) - \mathbf{w}^T(n)\mathbf{x}(n)$$

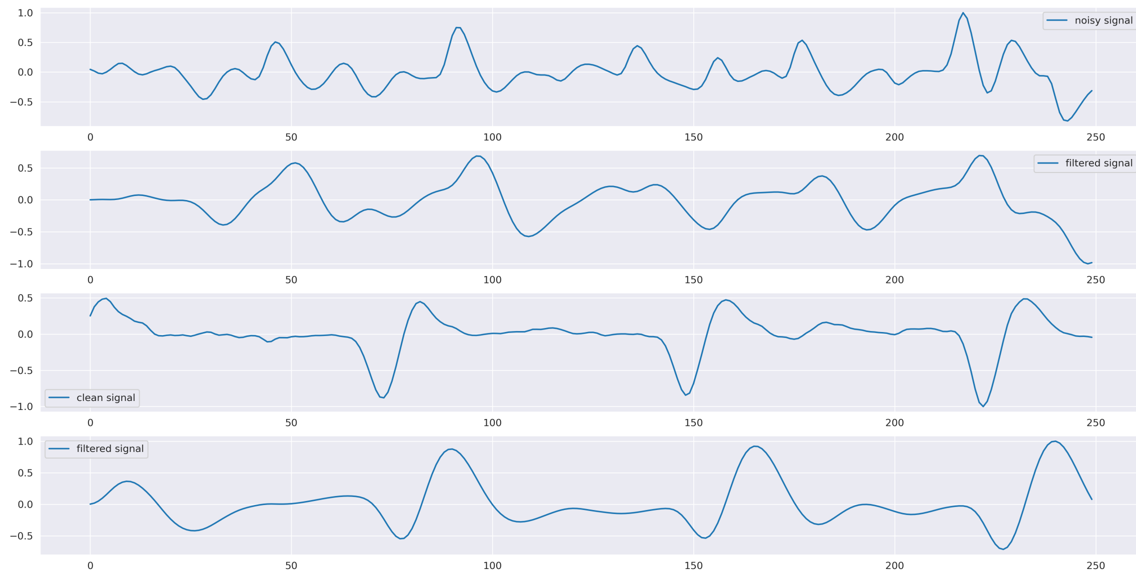

Fig. 4. Sample Low Pass Filter Response in Time Domain. The first plot demonstrates a sample of the PPG data(Red) affected by motion artifacts and the next plot shows the low-pass filtered data(4 Hz). Similarly, the third and fourth plot vertically demonstrates a sample of the normal PPG data(Red) and its filtered version respectively

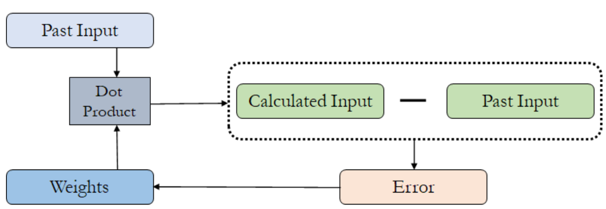

Fig. 5. Overview of LMS Filter

A visual description of the algorithm's application is shown in Fig-II-D.

LMS filter along with accelerometer signal data can be used to reduce motion artifacts in PPG signals [4]. The algorithm used in the project is described in II-D.

E. LMS and Accelerometer Integration

As noted in Figure-II-D, The raw PPG signal is first filtered using Low Pass Filter to reduce noise. Then the processed input is passed to the Adaptive LMS filter. For our project, it was a 10th-order LMS filter with a learning rate of .The order of the experiment is relatively high because taking fewer samples was inadequate to model motion artifact data. The weights of the adaptive filter are selected based on the motion information from the accelerometer. If there is no motion in the system, then the adaptive LMS filter keeps on using existing weights. But if there is a presence of motion, the LMS filter switches to different weights. The new weights are used to adapt to the motion artifacts. Once the motion sensors no longer detect signals, the filter switches to the default weight.

III. Implementation Details

In our study, we utilized a microcontroller-based system to collect sensor data from photoplethysmography (PPG) and accelerometer sensors. The microcontroller was initially connected to a computer via the Arduino Integrated Development Environment (IDE) to enable data collection. The collected data was then processed and analyzed in Python on the computer. Based on the results of the data analysis, we made design decisions for the project. The final project shown in Fig-II-D used the Arduino Uno microcontroller for the data processing and SpO2 estimation.

Initially, we tested various algorithms using Python on Jupyter notebooks. After thorough experimentation, we developed a computationally efficient version of the final algorithm and implemented it in Arduino.

To evaluate the performance of our algorithm, we compared the output of the PPG sensor with that of a commercial pulse oximeter reader (used as the gold standard). The initial SpO2 output without the proposed processing is used as the baseline for evaluation.

A. Costs

As with any engineering project, there were several costs associated with the implementation of our project. The costs for our project consist of the cost of the components and sensors used in the system, which is detailed in Table - II. Overall,

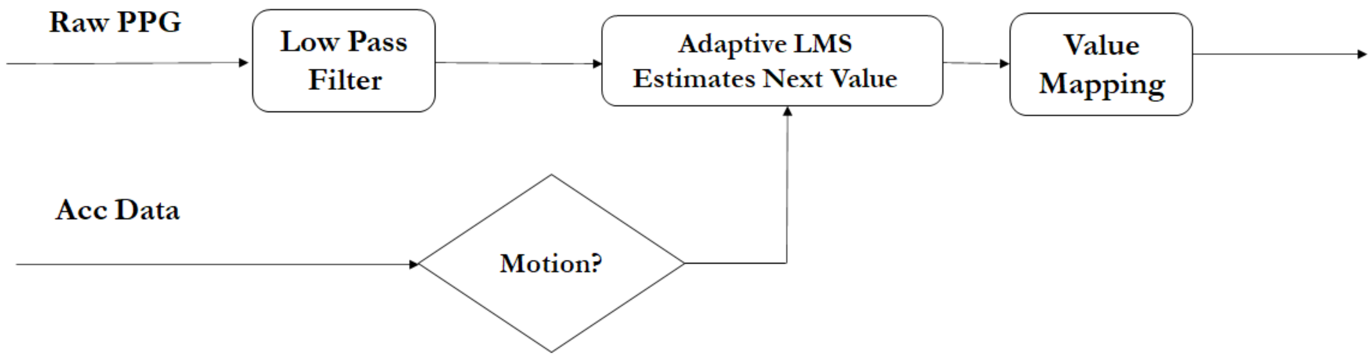

Fig. 6. Accelerometer and LMS integration

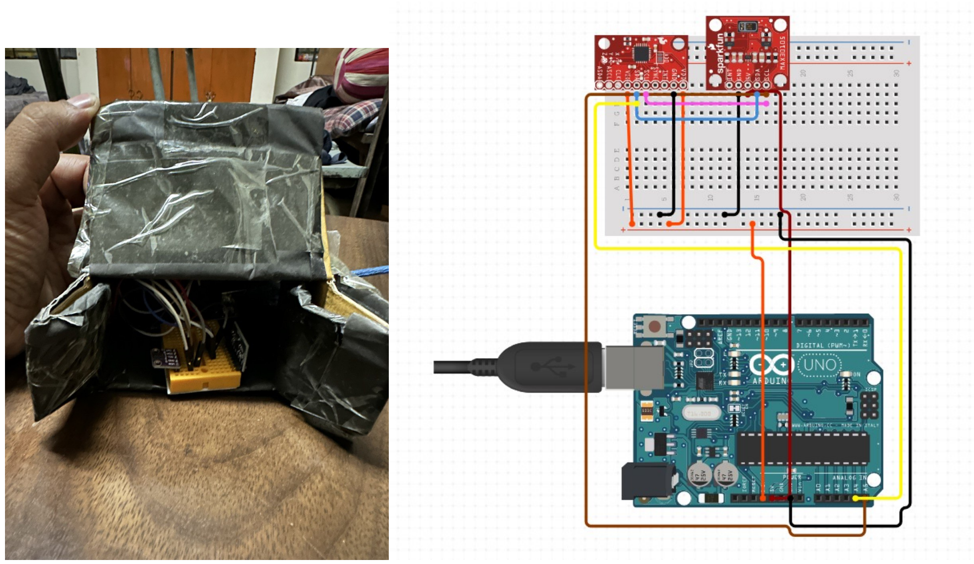

Fig. 7. Hardware Implementation

the total cost of our project is 2,685 BDT (approximately 25 USD).

B. Results

The results are examined manually. Upon inspection, our method shows improved performance over the baseline. The performance is very close to the gold standard method. Although this method is not completely immune to motion artifacts, their effects are significantly reduced and an overall improved result over the baseline is achieved.

IV. Future Works

While the project has shown promising results in improving SpO2 calculation, there are still several areas for future improvements. Firstly, the usage of more sophisticated algorithms such as RLS and NLMS can improve the performance even further. Additionally, the project can be built within a smaller enclosure for portability. The hardware enclosure can also be designed to reduce the impact of motions in the sensors, which would yield better results. The incorporation of more powerful hardware can also improve the processing time of the signals. Overall, there is still much work to be done in this field. We hope that this discussion of potential future directions will inspire further research and innovation in this important area of biomedical signal processing.

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