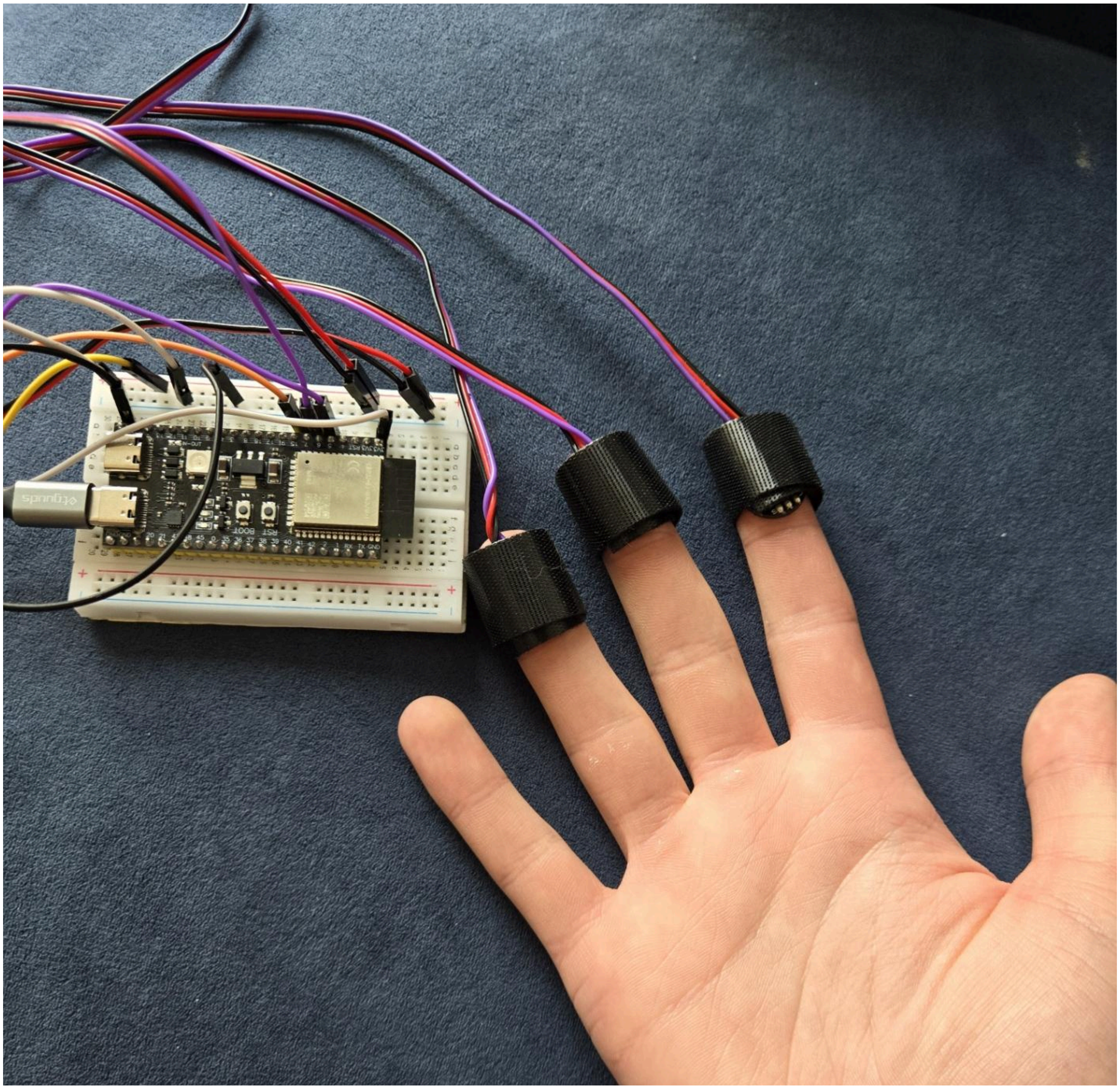
PPGlove: Denoising PPG Data using Multiple Sensors

Authors: Sameer Faruquee & Graham Grieb



Abstract

In this paper, we propose a multi-PPG system that takes readings on different fingertips to get a more accurate BPM reading. The goal of the multiple sensors is to reduce the influence of noise due to motion artifacts. We collected data from multiple PPG sensors placed on different fingertips with different amounts of motion. In general, we found that including multiple sensors was more accurate than individual PPG sensors when averaged in the long-run.

Introduction

Photoplethysmography commonly referred to as PPG is an optical technique that is used to characterize various physiological indicators including but not limited to Pulse Rate Variability (PRV), Blood Oxygenation (SpO2), and Respiratory Rate. In PPG, a Light Emitting Diode (LED) near or on the skin is used to transmit light into the tissue. Blood in the tissue can absorb or reflect the tissue. A photoresistor near the LED is used to measure the amount of light that is reflected from the tissue. The measurement reflects the dynamics of the cardiovascular system as changes in blood volume caused by the pumping of the heart change the amount of light reflected by the tissue. Thus, PPG can be used to noninvasively measure various cardiovascular indicators. The noninvasive nature of PPG has facilitated the inclusion of the technique into various commercial and academic devices and products. This growing ubiquity has made PPG a popular method for continuous health and fitness monitoring (Almarshad et al.).

While PPG has many applications, it is also very susceptible to noise which can reduce its reliability. A source of noise that makes PPG more difficult in the wild is motion artifacts. Motion artifact typically occupies the same frequency band as the cardiovascular cycle and its harmonics. Therefore, frequency based filters can be insufficient in removing this noise (Y. Zhang et al.). Prior work has shown that many algorithms can be used to abstract useful PPG signals from data contaminated by motion. However, these algorithms tend to be computationally expensive which hinders their applications to embedded systems (Hanyu and Xiaohui).

Due to the growing need to implement PPG efficiently into embedded systems for remote patient monitoring, we propose a new method to reduce noise in PPG data. Our system includes an array of PPG sensors on different fingers of the hand. We chose to assess PPG at the fingertips as that is used clinically and because finger tissue is relatively thin so light can penetrate it more easily (Nardelli et al.).

This system could also easily be implemented in a glove with PPG sensors sewn into the fingertips. This could allow for an easily worn system that could be used to measure biometrics in situations where the user would already be wearing a glove. This could be useful in colder climates where a user is wearing gloves to keep their hands warm or in hospital settings where gloves are worn as PPE. A user may want to track their BPM or other biometrics in these scenarios in order to track exercise, monitor stress, or for more specific health concerns. A glove is also the best location for a multi-PPG system as the fingers offer many different sites for PPG with similar pulse arrival times.

Related Works

In 2017, Hanyu and Xiaohui found that a statistical thresholding method can be applied to detect windows of PPG data that were likely to contain motion. Bandpass filtered PPG is periodic with the cardiovascular system, so windows that contain motion are likely to have a much higher skew, standard deviation, or kurtosis than windows that are uncontaminated. In their processing pipeline, they set a threshold for these values, and if any of the three statistics were greater than its respective threshold, that window was removed from the data. While this was successful in removing noise from the dataset, it also reduces the amount of data substantially since they do not recover the signal. In the wild, there is likely to be much more motion than in a clinical setting, so this drawback would be emphasized in a commercial solution. Additionally, by using statistical methods, there could be windows that are false positives or false negatives, so the composite signal may still be incorrect (Hanyu and Xiaohui).

One strategy for removing motion artifacts is to use an IMU to gather acceleration data at the PPG site. In this paper, they use singular spectrum analysis which is multidimensional in its computational complexity. Their heart rate error in this paper was 2.6 BPM, showing that signal reconstruction can be accurate when using an accelerometer (Z. Zhang et al.). While this approach was very accurate, it is very computationally expensive as different types of sensors require more memory and this method involves creating multiple matrices which would consume much of the memory on an embedded system.

Another common strategy for denoising PPG signals in order to analyze heart rate and other indicators is to use a sensor with multiple wavelength light emitters and receivers at the same location. One signal is used as a reference signal and another as a primary signal. In this paper, an adaptive transversive filter is used to modify the reference signal to match the noise of the primary signal. The output of this filter is then subtracted from the primary signal in an effort to isolate the signal of interest (Barreto et al.) . Many modern systems use a similar system, but use different wavelengths of light for the different sensors. In this method, they take advantage of the fact that certain wavelengths penetrate deeper and therefore have a larger amplitude in their motion artifacts. This means they are better used as a reference signal. In this paper, they use the green PPG as the primary signal and the red PPG sensor as a reference signal for noise. This red PPG is more affected by motion artifacts as it penetrates deeper (Park et al.).

While multichannel PPG with multiple wavelengths can be used to effectively reduce motion artifacts, these methods often rely on data processing methods such as Singular Value Decomposition, Independent Component Analysis, and Principal Component Analysis (Lee et al.). These methods often have computational complexities that are 2nd or 3rd order or above, which hinders their application in real time applications.

In 2022, Suboh and colleagues found that derivatives up to the fourth derivative can also be used to characterize the peaks of the PPG waveform by analyzing where the derivatives have inflection points. This could also be used to either validate a composite waveform or detect if a PPG waveform is liable for containing motion artifacts (Suboh et al.).

These works show there are numerous methods to reduce motion artifacts in PPG but these methods are generally computationally expensive which makes them difficult to implement in real time. We aim to combine learnings from these works to create a computationally efficient method to denoise PPG.

Methods

Our device uses an ESP32-S3 microcontroller (MCU) that powers and reads 3 analog PPG sensors placed on the user's pointer, middle, and ring finger. The ESP32-S3 was chosen due to its capabilities to power all of the sensors consistently and having enough ADC's to read all of them. The PPG sensors used were part of The Pulse Sensor Kit. ECG was also taken as a ground truth using the DFRobot Gravity ECG Sensor. The ESP32 has WiFi capabilities which allows us to extract data through a web server. PPG will be measured at a sampling rate of 150 Hz for 15 second windows. We chose to use a window of 10 seconds to have a 0.1 Hz frequency resolution to refine our analysis.

Sensor data will be normalized to have a mean of 0 and a standard deviation of 1. All sensor signals will be passed through a bandpass FIR Filter with a passband of roughly 0.5-6 Hz (Hanyu and Xiaohui). We choose to use an FIR to minimize phase distortion in each of the signals. After filtering, the transient response due to the filter will be removed from the data.

We will then calculate standard deviation, kurtosis, and skew of the signals based on the method applied by Hanyu and Xiaohui. After calculating these statistics, we use these to create weights to create a weighted average (Hanyu and Xiaohui). If a signal includes heavy motion artifacts, as indicated by its statistics, then it is given a lower weight in the ensemble average.

Our system will use ensemble averaging in the frequency domain to reduce random noise due to motion in each of the fingers. We will apply a Hamming function of the data to remove edge effects in the data. Then, we will calculate the FFT of each finger's signal, and average the amplitude of each signal. By averaging amplitudes, we can ignore phase differences in each of the fingers. We will then inverse the FFT to transfer the data back to the time domain using the averaged amplitude and the phase spectrum of the signal with the lowest amount of noise. We apply a 10 point moving average filter and remove 10 points at the beginning and the end to minimize random peaks. In theory, this will create a time domain signal with random fluctuations due to movement in the fingers removed.

For our study we will collect various sensor measurements from both PPG as well as ECG. ECG will be used as a gold standard to compare PPG measurements. We will collect the following datasets:

1). Minimal motion in fingers
2). Tapping with one finger
3). Random tapping with all fingers.

We will collect three 3-minute sets of each. After processing we will calculate PPG heart rate and compare each to the ECG heart rate in each window. We will also reconstruct the PPG based on our method and compare its calculated heart rate to ECG heart rate.

Results

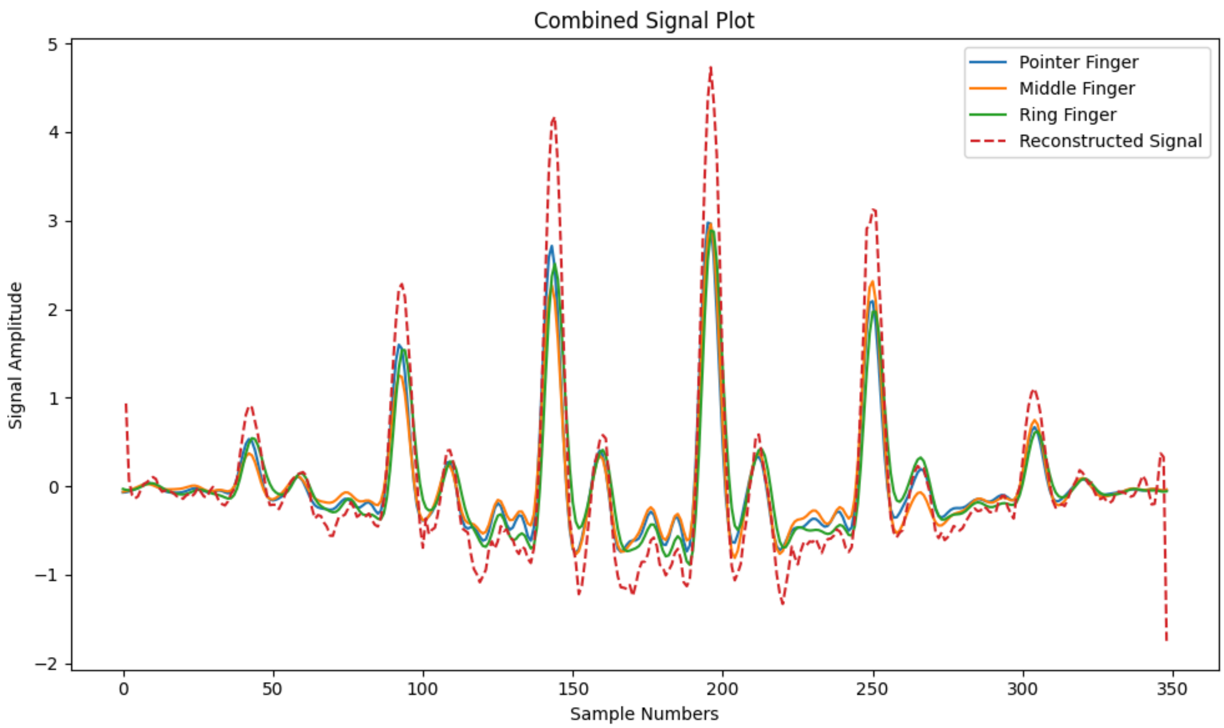


Fig 1. Filtered PPG Signals and Reconstructed PPG in First Window in No Motion Dataset

Figure 1 shows the reconstruction and each of the individual PPG signals in a dataset with no motion. We used the no motion dataset to verify that there were no errors in the reconstruction. Generally, the reconstruction captures the shape of the original data well. Interestingly enough, it seems that the reconstruction has sharper peaks than the original data even though both have been normalized.

Table 1. BPM error values between PPG and ECG for all fingers and reconstructed waveforms

Finger	Pointer	Middle	Ring	Reconstructed
BPM Error - No Motion	8.5 +/- 10	10.5 +/- 7	11 +/- 10	5 +/- 6

BPM Error - Pointer Tap	26.5 +/- 30	-22 +/- 20	9 +/ 12	8 +/- 10
BPM Error - All Fingers Random	22 +/- 36	21.5 +/- 30	-13 +/- 20	11.5 +/- 16

Table 1 shows the data we gathered by comparing PPG heart rate to ECG for multiple types of datasets. BPM Error is defined at PPG Heart Rate - ECG Heart Rate. The table aggregates all 3 copies of each dataset into one. The statistics were calculated window by window for each dataset. In total, the sample size is roughly 54 windows for no motion, pointer tapping, and all fingers tapping.

Discussion & Next Steps

We found that in general the reconstructed signal did generally perform better than the individual fingers. However, when we observed each of the individual windows, the reconstructed would generally perform worse than at least one of the individual fingers. For example in one window in pointer tapping we found:

Reconstructed PPG BPM error: 3.7 BPM
Pointer PPG BPM error: 30 BPM
Middle PPG BPM error: 6 BPM
Ring PPG BPM error: 1.2 BPM

In this particular window, the ring finger PPG was more accurate than the reconstruction. However, it seems the reconstruction generally performs better over repeated trials.

Based on Table 1, there seems that there is some improvement in the PPG accuracy when using the reconstruction when there is motion, however, this improvement does not seem to be significant. More data needs to be collected to verify this method.

It seems that the PPG errors were quite high in general, and often overestimated the heart beat. It seems that this might be due to the low window size as a low number of peaks are captured in each window. In the future, more testing can be done to fine tune the exact window size and filter order that would have the best time-resolution and frequency-resolution balance to optimize the accuracy.

Currently the reconstruction of the 3 PPG's is done post data collection. The first step to take in the future would be to get this signal processing pipeline working live on the MCU as it records PPG data. Our current MCU, the ESP32-S3, likely has ample enough computing power to handle this. Our current data processing is running in Python using libraries coded in Python. These would need to be switched to C/C++ to be able to run on the ESP32.

The final steps would be to assemble the sensors into a glove unit. In this glove, we would likely have PPG sensors sewn at each fingertip with all of them connected to an MCU at the back of the hand. This unit could have an OLED to display the user's biometrics or could have a wireless antenna to connect to a phone and display it on an app. Power would be a concern in this step. We will need to power the glove through a battery and optimize our MCU and sensors to be as power efficient as possible to maximize battery life. This glove could also be further extended to have multiple sensors on each finger which would allow us to extrapolate Pulse Transit Time.

Conclusion

We were able to collect BPM metrics that were more resistant to motion due to the use of multiple PPG sensors. The next steps of this project would be first to get real-time signal processing working while taking PPG readings. The final step would be to assemble a final product in an actual glove unit. Additionally, more data needs to be collected from a larger population performing a greater variety of activities. Additional, fine tuning of the processing variables is also required to optimize the model. In general, it seems ensemble averaging of PPG sensors might show promise in low complexity PPG denoising.

Works Cited

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