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Multi-Modal Physiological Sensing on the Upper Arm

Kimberly L. Branan[a], Gilberto O. Flores Reyes [b], John A. Abel[a], Madhav Erraguntla [c], Ricardo Gutierrez-Osuna[d], Gerard L. Coté[a,b,e]
[a]Department of Biomedical Engineering, Texas A&M University, College Station, TX; [b]Department of Electrical & Computer Engineering, Texas A&M University, College Station, TX; [c]Department of Industrial & Systems Engineering, Texas A&M University, College Station, TX; [d]Department of Computer Science and Engineering, Texas A&M University, College Station, TX; [e]Texas A&M Engineering Experiment Station, Center for Remote Health Technologies and Systems, College Station, Texas, United States

ABSTRACT

Wearable technology provides fitness information and, in some cases, continual access to tracking and monitoring of cardiac health to physicians and patients. However, wearable methods suffer from motion artifacts. To address this issue, we have developed a multi-modal system using the combination of (1) PPG with three wavelengths of light (green, red, and IR at 527, 660, and 880 nm), (2) bioimpedance, and (3) single-sided ECG to measure heart rate (HR) on the upper arm. This study investigated measuring HR under conditions of sedentary motion and micro-motion (e.g., typing). We compared the system with signals acquired from commercial wrist and chest devices, verifying the accuracy of the HR measurement for each anatomical location. This multi-modal approach investigated the wavelength of light chosen to provide the most accurate HR measurement and assessed cross-correlation to minimize motion artifacts. Results indicated the green PPG and SS-ECG modalities have the lowest mean absolute error (1.0 & 2.0 bpm, respectively) relative to the chest device during typing conditions compared with the wrist device and other upper arm modalities.

Keywords: three-wavelength PPG, bioimpedance, single-sided ECG, heart rate

1. INTRODUCTION

Cardiovascular disease (CVD) is considered the leading cause of death worldwide, with approximately 17.9 million lives a year lost to CVD, according to the World Health Organization (WHO) [1]. To monitor and diagnose cardiovascular health, and help prevent CVD, metrics such as heart rate (HR) are used. Traditionally, this metric is measured with a twelve-lead electrocardiogram (ECG) in a clinical setting, using long leads connected to wet electrodes, which are placed in specific positions on the chest [2]. Unfortunately, wet electrodes can irritate the skin if worn too long, and the system's leads limit patient mobility. Long leads can be avoided by using wireless ECG chest patches [3], thus allowing patients to have increased mobility. However, the adhesive must be changed out and often irritates over time, especially for active patients.

To counter both of these issues, non-adhesive wearable technology can potentially provide a solution that allows a patient mobility without the risk of irritating the skin with a patch or an electrode. However, non-adhesive wearable devices have increased sensitivity to motion artifacts, which often cause a miscalculation in HR since spikes due to motion artifacts may be mistaken as heartbeats. To address this issue, we propose a multi-sensor system that measures three independent HR biosignals in the upper arm. The hypothesis is that signals measured from the upper arm are less sensitive to motion artifacts than other measurement locations. Within this preliminary study, only micro-motions and their effect on the accuracy of HR calculations will be examined. In one definition, micro-motions are considered to be those that come from small movements, such as tapping or typing, and are not typically registered by an accelerometer [4-6]. On the other hand, there are macro-motions defined as more significant movements, such as those from physical activity (e.g., walking, running) which can be registered by an accelerometer. Both types of motion cause low-frequency signals between 0.1 – 20 Hz which is within the frequency range of the measured HR biosignals [7]. By measuring biosignals collected from three separate modalities, photoplethysmography (PPG), single-sided electrocardiogram (SS-ECG), and bioimpedance (BioZ), we can determine which modality is affected the most by micro-motions and whether HR can be accurately calculated using a multi-modal sensing system on the upper arm.

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PPG is a system that utilizes light to capture a change in blood volume within the area of interest. A typical system is comprised of an LED and photodiode, and the wavelength of light is usually green, red, or infrared [8]. This study will utilize a sensor that contains all three wavelengths. SS-ECG measures the electrical impulses which occur during the cardiac cycle. A typical setup can consist of 2 or 3 gel or dry electrodes placed along the arm to capture these electrical impulses [9]. BioZ measures the impedance change caused by an applied AC signal and the tissue composition of the region of interest. In this study, BioZ is utilized to measure impedance plethysmography, the electrical impedance change that occurs with blood volume changes [10]. The BioZ signal can be measured using gel or dry electrodes. Within this preliminary study, we will focus on using gel electrodes for both the measurements of SS-ECG and BioZ to show the proof of concept in terms of measuring HR from the upper arm sensing system under sedentary and micro-motion conditions, such as typing.

2. MATERIALS AND METHODS

2.1 Upper Armband System

The proposed system combines three modalities to measure HR: PPG, SS-ECG, and BioZ. PPG measurements are based on a MAX30101 system (MAXIM Integrated) and contain green, red, and infrared (IR) LEDs at 527, 660, and 880 nm, respectively. The MAX30101 chip samples the PPG signal with an onboard 18-bit ADC before data is transmitted to a Nucelo64-L412KB (STMicroelectronics) microcontroller (MCU) via I2C. SS-ECG measurements are based on an AD8232 (Analog Devices) analog front end in the three-electrode configuration, with the analog signal being sampled with a 12-bit ADC on board the MCU. PPG and SS-ECG signals are sampled at 100 Hz with the MCU, and data is stored onto an SD card. The BioZ system consisted of a fabricated four-wire bioimpedance circuit with injected current and voltage measured from the subject. The injection current is at a frequency of 18.4 kHz. The measured voltage is acquired with an instrumentational amplifier and sampled at 100 kHz with a NI-DAQ (National Instruments) containing a 16-bit ADC. Data collected with the NI-DAQ is directly imported into a PC. The system is battery-powered and was only tethered to a PC for data transmission.

To collect all the signals with an SNR greater than 2.5, we evaluated different sensor locations and we selected those shown in Figure 1. The PPG sensor and the four gel BioZ electrodes are placed along the brachial artery within the upper arm. Three gel SS-ECG electrodes are placed orthogonal to the top BioZ electrode proximal to the shoulder (Figure 1a).

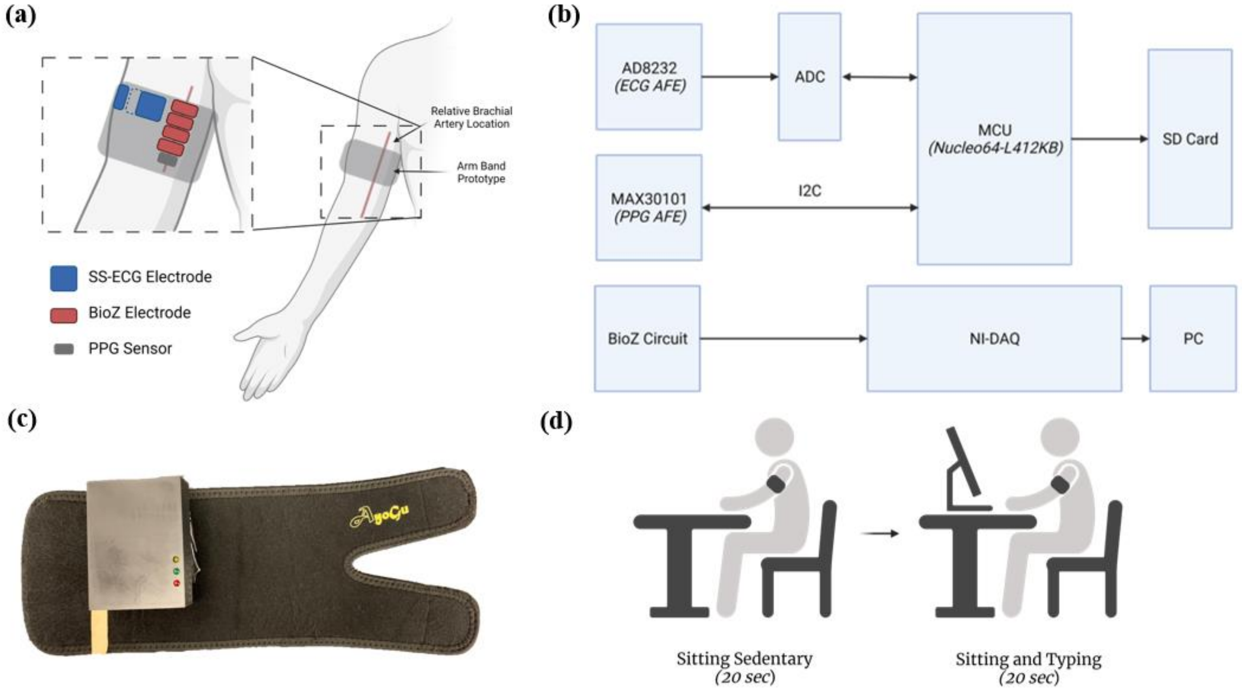

Figure 1. (a) Relative locations of the sensors along the upper arm. (b) Integration of sensors within the system. (c) Device that was positioned on the upper arm. (d) Motion artifact characterizing protocol. Image created with biorender.com.

2.2 Motion Artifact Study

To study how the addition of motion would affect the signal quality of the three HR signals on the upper arm, a single subject was asked to remain sedentary and then perform typing on a computer keyboard, capturing both at rest and micro-motions. All trials consisted of 20 seconds of simultaneously collecting SS-ECG, PPG, and BioZ signals. Three trials, which were captured temporally close together to maintain a constant HR, were collected for sedentary and motion scenarios (Figure 1d). During all the trials, a wrist device, which captured a green PPG signal, and a chest strap, which captured an ECG, were worn to compare signal quality at different locations. All systems used to measure signals were timestamped so that all data could be accurately correlated.

2.3 Signal Processing and Heart Rate Analysis

All collected data were processed using MATLAB 2021a. The PPG signal was digitally filtered with a Butterworth low pass filter (LPF) with a cutoff frequency at 5 Hz before the lower envelope of the signal was removed to filter the baseline wander and DC offset imposed on the AC signal of the waveform. HR was calculated by determining the number of systolic peaks within the filtered AC signal that occurred in the 20-second timeframe. In turn, the SS-ECG signal was filtered with a Butterworth LPF with a cutoff at 30 Hz, followed by a continuous wavelet denoising filter, which used a syms 4 wavelet at a level 8. The filter allowed the extraction of the R-peaks within the SS-ECG, which were used to measure HR. Lastly, BioZ was processed by extracting the real component from the collected signal before digitally filtering it with a Butterworth LPF with a cutoff frequency of 5.7 Hz. As with the PPG signals, the lower envelope of the BioZ signal was removed to eliminate the baseline wander and DC offset. Finally, the first derivative of the signal was acquired to determine the HR by determining how many troughs occurred in the signal.

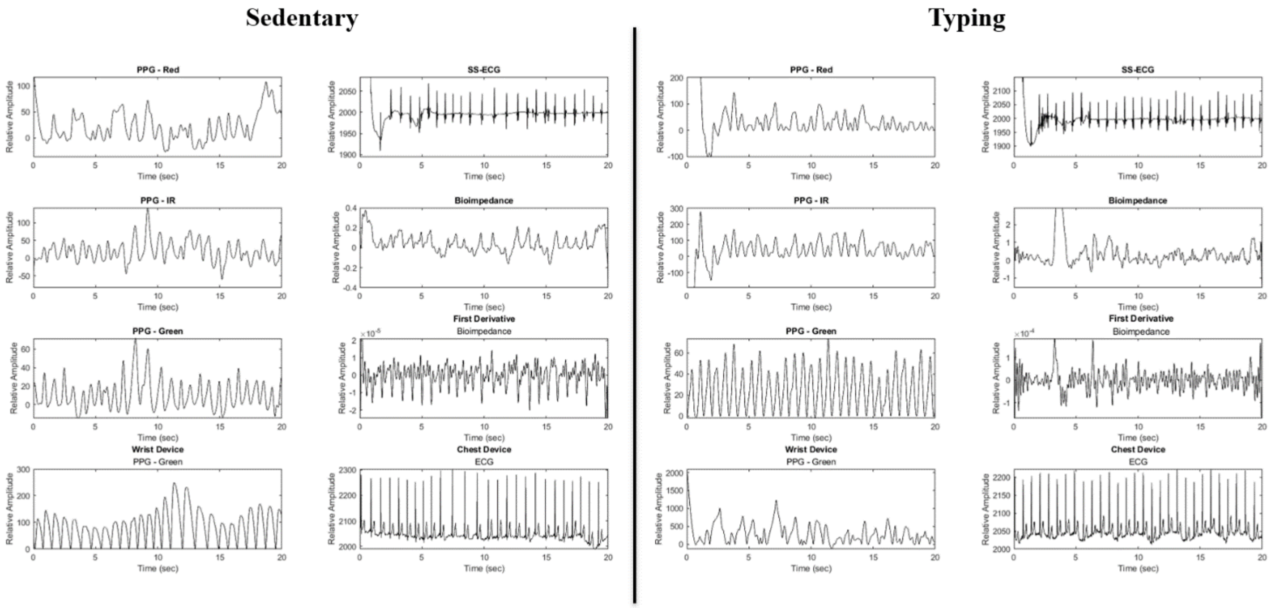

Figure 2. Typical traces of all 8 signals (PPG – Red, PPG – IR, PPG – Green, Wrist Device, SS-ECG, Bioimpedance, First Derivative of Bioimpedance, and Chest Device) for both sedentary and typing conditions after signal processing.

The average and standard deviation of HR from the three trials were calculated to estimate the repeatability of each modality under the two motion conditions. Mean absolute error (MAE) was also calculated to determine the accuracy of the upper arm modalities and wrist device relative to the chest device.

3. RESULTS AND DISCUSSION

Three trials were collected for each of the two motion conditions: sedentary and typing. Results are summarized in Table 1. As shown, in the sedentary trials all modalities had a standard deviation smaller than or relatively equal to the chest device, indicating a good degree of repeatability for the three modalities. However, it is noted that when calculating HR, only 20 seconds of data were collected for each modality for each trial. Because of this, there is a level of error that can be associated with the short sample period. A single beat missed within any modality would result in a 3-bpm difference from the reference value. Further, the location difference from chest to arm causes a slight time delay when collecting signals which could, in turn, cause a miscalculation of heart rate by 3-bpm because one beat was missed. All modalities have a standard deviation smaller than 3-bpm, confirming the repeatability of the systems.

Table 1. Average and standard deviation (STD) for all three sedentary and typing trials.

	Sedentary		**Typing**	
Modality	Average *(bpm)*	STD *(bpm)*	Average *(bpm)*	STD *(bpm)*
PPG - Red	77.0	1.41	80.0	1.41
PPG - IR	76.0	1.41	85.0	3.74
PPG - Green	76.0	2.86	82.0	3.74
SS-ECG	76.0	1.41	84.0	4.90
BioZ	76.0	1.41	80	3.74
Wrist Device	75.0	2.45	74.0	2.83
Chest Device	74.0	2.83	82.0	3.74

When compared with the chest reference for typing trials, all modalities except for SS-ECG have a smaller or equal standard deviation. The SS-ECG overestimated the HR for two trials by counting an extra peak, causing the standard deviation to be higher. When comparing the standard deviations of each modality during sedentary and typing, it was clear that the typing showed an increase in the standard deviation except for PPG – red, whose standard deviation remained constant. The increase in standard deviation is attributed to motion and physiological effects such as induced stress while typing causing the heart rate to increase.

The accuracy of each modality was determined by calculating the MAE using the chest device as the reference. Results are shown in Table 2. Comparing the MAE for the sedentary trials resulted in all modalities exhibiting an error smaller than 3-bpm except for the red PPG measurement. The wrist device had the lowest MAE (1.0 bpm) relative to the other PPG signals collected on the upper arm in the sedentary setting. This observation is attributed to the low-frequency noise having a higher amplitude on the upper arm than on the wrist when utilizing PPG. This low-frequency noise is likely due to the respiration rate removed from all signals by filtering the DC component before HR is calculated [11]. Another possibility is that the SNR of the signal acquired on the wrist is higher than signals collected on the upper arm. A higher SNR is due to the depth of the vascular bed on the wrist versus the upper arm and the tissue composition differences of each measurement location [7]. The wrist has a shallower vascular bed relative to the upper arm causing a larger SNR for signals acquired on the wrist.

Table 2. MAE for sedentary and typing motions with the chest device as the reference system.

Modality	**Sedentary** *(bpm)*	**Typing** *(bpm)*
PPG - Red	5.0	4.0
PPG - IR	2.0	3.0
PPG - Green	2.0	1.0
SS-ECG	2.0	2.0
BioZ	2.0	4.0
Wrist Device	1.0	8.0

In terms of how typing affected the ability of different measurements to collect HR, the wrist device had the largest MAE (8.0 bpm) while the green PPG signal acquired from the upper arm had the smallest (1.0 bpm). Overall, the upper arm IR and green PPG signals and the SS-ECG signal can accurately calculate HR when compared with the reference device. Micro-motions such as typing affect the signals acquired from the wrist more than those collected from the upper arm. This is in part due to the upper arm remaining relatively stationary compared to the wrist during typing.

Overall, the red PPG signal had the largest MAE compared to all other signals collected on the upper arm. Red is a longer wavelength relative to green, making it more prone to measuring motion artifacts [12]. This result was also observed when comparing the IR and green signals for typing. The IR MAE is larger than the green MAE since the depth of penetration of the IR signal is larger than the green causing the IR signal to acquire more motion artifacts. The SS-ECG modality had a constant MAE between the sedentary and typing conditions. The IR PPG signal and the BioZ signal had increased MAE between the sedentary and typing motions indicating the signals are more affected by smaller motions than the SS-ECG and green PPG signals.

4. CONCLUSION

This study utilized a multi-sensor device for the upper arm containing PPG, SS-ECG, and BioZ sensors, and compared it against a chest device and wrist device to determine the effect of motion artifacts on HR signal quality from different locations. Two motion conditions were studied, sedentary and typing. In both cases, 20-second signal segments from each modality were collected simultaneously. All systems proved to be repeatable in calculating HR, but the SS-ECG and green upper arm PPG sensor had the lowest error during typing, whereas the wrist device had the largest. This suggests that the upper arm modalities are not as affected by micro-motions (such as typing) as a wrist device, allowing for the potential for more accurate calculation of HR under micro-motion conditions. Future studies will include repeating the protocol for extended periods and performing the study on multiple subjects to confirm the findings of this preliminary study.

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