APOLLO: NON-INTRUSIVE VITAL SIGN MONITORING USING SMART TEXTILES

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Abstract

Accurate vital sign detection systems are critical for rapid emergency response and early identification of diseases. However, vital sign monitoring accuracy and intrusiveness often go hand-in-hand. To address the need for accurate, non-intrusive vital sign detection, we introduce Apollo, a wearable vital sign monitoring system using sensors made from conductive textiles. The current version of the Apollo system is capable of accurately estimating respiration rate with a weighted average error rate of less than 1 breaths per minute for sedentary activities, and a weighted average error rate of less than 1.5 breaths per minute while subjects walk. The current version of Apollo is capable of measuring heart rate with less than 5.5 beats per minute for certain sedentary activities, and we thoroughly discuss possible design changes to improve heart rate detection accuracy in later versions of Apollo.

Introduction

When emergencies arise dealing with heart irregularities or respiration difficulties, mere seconds can be the difference between life and death. In non-emergency scenarios, irregular heart or respiration events can be symptoms of underlying diseases which sometimes benefit from early-onset treatment. As a result, the ubiquitous computing community has made a continuous effort over the past decade to develop vital sign monitoring systems that are real-time sensitive, accurate, and non-intrusive. The first step when developing these sensing platforms is measuring vital sign measurement accuracy with healthy subjects.

One of the main challenges opposing such work is that accuracy and intrusiveness tend to go hand-in-hand. For example, the Holter monitor[10] is a highly-accurate, portable ECG device used by medical professionals and astronauts alike. However, semi-flexible wires and electrode contacts reduces the level of comfort of the wearer. Smartwatches are significantly more comfortable, but measure heart rate with less accuracy than the Holter monitor. Contactless means of measuring vital signs are non-intrusive, but tend to be less robust when subjects are in diverse environments.

To mitigate this accuracy/intrusiveness tradeoff, we introduce the fifth design generation of the Apollo vital sign monitoring shirt which leverages a combination of physical contact with the wearer with soft conductive textiles to provide an accurate vital sign monitoring system for the wearer while being minimally intrusive. The properties of conductive textiles change upon application of different types of physical stress such as pressure or stretch forces; such forces include those generated by expansion or compression of the chest during respiration. Combined with modern signal processing techniques, we can extract the respiration and heart rate events using sensors built with no rigid components.

We provide a preliminary evaluation of Apollo using data collected from a small user study and compare our results with prior works. Additionally, we discuss the limitations of Apollo and introduce possible solutions for future work as well as specific medical applications.

In summary, this paper discusses the following:

1. Design and methodology for Apollo, a wearable vital sign monitoring shirt
2. Analysis of the accuracy of our design using data collected from a small user study
3. A discussion of how Apollo compares to prior research, and how we can further improve our system

Vital Sign Monitoring Shirt Design

In this section, we discuss the hardware used in the assembly of Apollo as well as the hardware used to collect ground truth information during our user study.

Base Clothing

Spandex-blend compression shirts are comfortable and are worn for all manner of activities including exercise, working, and sleeping. The base shirt that is used for APOLLO is an Under Armour short-sleeved athletic compression shirt; this base shirt serves two purposes. First, compression material is more form-fitting than regular non-compression shirts and will conform to the wearer's body shape. People with different body shapes can fit into the same-sized compression shirt without the material being baggy in certain areas. This is often not the case with non-compression shirts that are not custom tailored to the wearer.

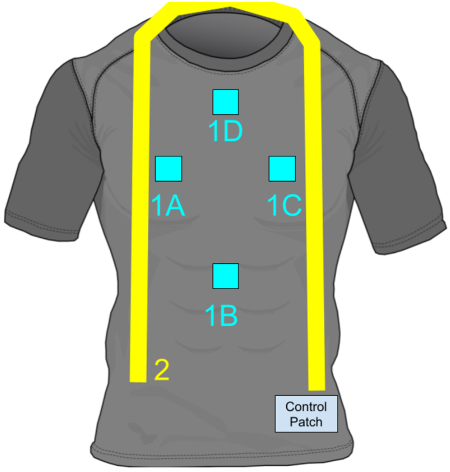
Second, the compression material increases the probability that the pressure sensors and stretch sensor remain in contact with the wearer at all times regardless of level of activity. This is an important design consideration since higher intensity activities such as running or biking will cause non-compression materials to "flop around".

Conductive Textile Sensors

There are two types of sensors sewn into our base shirt: three pressure sensitive patches and one stretch sensitive strip. The pressure sensitive fabric[3] used experiences a decrease in resistance when pressure is applied, and the stretch sensitive fabric[14, 15] experiences a decrease in resistance when a stretching force is applied. When working with conductive textiles, it is important to note that these textiles have a maximum and minimum possible resistance which is dependent upon the dimensions of the fabric piece and the number of layers of the fabric. After a certain amount of force is applied, no additional resistance changes will be measurable. We will call this the "saturation limit" of the sensor.

To create a single pressure patch, we sew two 2in x 2in squares of pressure sensitive fabric back-to-back. This increases the maximum amount of pressure we can apply to a pressure patch before the saturation limit is reached. These pressure patches are sewn on the inside of the shirt so that chest and abdomen push the pressure patches against the compression material of the base shirt.

Our stretch sensitive fabric comes sliced into 12cm x 12cm squares. We cut these fabric squares into 12cm x 2cm rectangles which are then connected end-to-end to create one long stretch sensor (length depends on the size of the base shirt). Our stretch sensor is sewn onto the outside of the shirt primarily to avoid interfering with the connections of the pressure patches.



(a) Sensor Layout

(b) Fabric Pressure Sensors

APOLLO is in its fifth design phase; Figure 1a shows the location of each fabric sensor and figure 1b shows the inside of a large-sized APOLLO shirt. Please note that the stretch sensitive fabric is not show since the inside of the shirt is displayed and the stretch sensitive fabric is sewn to the outside of the shirt. Stretch sensor 2 is run vertically up/down the chest to allow for accurate readings from users with varying body types. Different body types can fit into the same compression shirt. As a result, the chest or abdomen circumference of each user may vary. In preliminary testing, we discovered that horizontal stretch sensors placed around the circumference of the chest and abdomen were less effective depending upon the body type of the wearer.

We have four pressure patches 1A-D, but technically only three pressure sensors since 1A and 1C are in series. 1A and 1C are in series since the signals generated by these patches individually were nearly identical during prototype tests.

This is most likely the case because the chest expands symmetrically. 1B is placed near the center of the abdomen and is particularly useful if a user "belly breathes" rather than displaying chest breathing.[2] 1D can be very useful for extracting heart beat ballistic events if the user does not have a large, protruding upper chest. This can create a small gap between the compression material and the neck at the neckline which reduces the contact of the user with sensor 1D.

Control Patch

A control patch located on the left hip of the Apollo shirt records voltage readings for all four fabric sensors. These readings are transmitted via Bluetooth Low Energy (BLE) to either a smartphone or another BLE capable device such as a laptop. In order to remain as non-intrusive as possible, the control patch uses as few rigid components as possible. The control patch contains a CurieNano[1] microcontroller, a battery, four resistors, and a voltage converter. These components are encased in automotive headliner foam to increase user comfort. The CurieNano is an Arduino based microcontroller containing six analog pins (for sensor measurements), a BLE module, a 6-axis accelerometer/gyroscope, and a 3-axis compass. The control patch is detachable so that the shirt can be washed.

Conductive thread[4] is used to connect the control patch components to the fabric sensors; this conductive thread is nearly as flexible regular sewing thread and allows us to connect components without wires.

Ground Truth Hardware

The ground truth for heart beat ballistic signals is recorded using a Polar H10 heart rate monitor.[5] The Polar H10 has been validated against ECG to record heart rate, RR interval data, and timestamps of heartbeats with an error less than 2 milliseconds. The Polar H10 is worn at the base of the sternum just below the pectoral muscles. To collect ground truth data for respiration, subjects in our study wore a microphone inside their N95 or equivalent mask to record respiration audio.

Related Work

Research into non-intrusive vital sign monitoring systems can be separated into two different categories: direct physical contact and contactless methods. There are advantages and disadvantages for each category. Methods involving direct physical contact tend to be more robust to environmental changes since the system moves with the wearer; systems requiring contact with the users are inherently more intrusive than systems that are contactless. Contactless vital sign monitoring systems can be highly influenced by changes in the environment, but are by definition non-intrusive. Since Apollo is a wearable vital sign sensing platform, we limited our related work to include only other wearable devices. Since our platform only monitors heart and respiration rate, we've excluded wearable devices that only monitor body temperature, blood oxygen levels, and/or blood pressure from our related work as well.

Direct Contact Methods for Vital Sign Monitoring

Acoustic Based Sensing Platforms: Microphones integrated into wearables have been shown to collect sufficient audio data to detect both heart rate[9,29] and respiration rate.[20,32] However, noise from uncontrolled environments can introduce noise into the audio generated by heart beat ballistic signals and audio from expansion/contraction of the diaphragm.

Accelerometer Based Sensing Platforms: Accelerometers are one possible type of sensor that can be used to extract heart and respiration rate. Several works have used 3-axis accelerometers placed in varying locations on the chest/abdomen to record diaphragm motion during respiration,[7,11,12,16–18,23,26] achieving between 80-100% accuracy for estimating respiration rate for sedentary activities such as sitting or lying down. Accelerometers have been shown to detect heart beat ballistic signals causing micro-vibrations through the chest and abdomen. Chest-worn[16,18,23] and wrist-worn[33] systems have achieved less than 5bpm and 9bpm error, respectively. Accelerometers show promise as viable sensing platforms to estimate heart and respiration rate; however, they are yet to be validated for high intensity activities.

Conductive Materials Based Sensing Platforms: Conductive textiles/materials integrated into clothing or sensing patches provide non-intrusive sensing platforms with minimal rigid components. Respiration rate can be measured using textile based stretch sensors,[22,34] graphene-based humidity sensors,[24] textile based pressure sensors,[19,26,27] or textile based ECG sensors.[6,27] The two works most closely related to Apollo are Phyjama[19] and Phymask.[27] Phyjama obtained a heart rate error of less than 2.5beats per minute (bpm) and a respiration rate of less than 1bpm during their sleep study. Phymask boasts an impressive heart rate error of 1.7bpm with a respiration rate error of 1bpm.

With conductive textiles, durability is the primary concern especially with the possibility of sen-

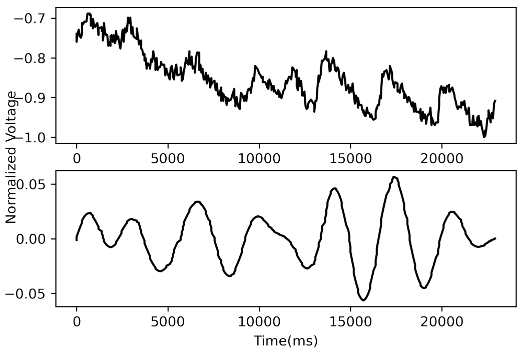


Figure 2: Raw Signal Filtering Using Butterworth Filters

sor degradation from being washed multiple times. Continued research into increasing the robustness of conductive textiles certainly necessary.

Signal Processing and Vital Sign Estimation

The signal data collected from the four textile sensors can be influenced by more than just respiration and heart beat ballistic events: posture, body shape, body movement, and even talking can add noise to the data stream. As such, signal processing methods must be used to extract the heart and respiration rates from the raw data signals.

Respiration Rate Estimation

We have four sensors that are sensitive to breathing, so we can generate a respiration rate estimation for each sensor individually. Estimating respiration rate for each individual sensor requires three steps. First, we use fast fourier transform (FFT) on the sensor waveform to extract the dominant frequencies; we select the most dominant frequency in the range of 12 to 40 breaths per minute. 12 to 40 breaths per minute accounts for an activity range from sedentary to high intensity. Once we have the dominant frequency, we use a 5th-order lowpass Butterworth filter[8] using our dominant frequency to remove higher frequencies from the sensor waveform. Figure 2 shows the transformation from the original (normalized) waveform for a section of data collected from pressure sensor 1AC and the filtered waveform.

The dominant FFT frequency within the range of normal respiration is used to select sliding window distance used by SciPy's peak detection algorithm[31] or the PYAMPD peak detection algorithm.[28] The results achieved with each of these algorithms were nearly identical. Figure 3 shows a plot of the filtered voltage readings from stretch sensor 2 while a subject was standing. The blue lines represent the timestamps for our inhalation events and the orange lines represent the peaks found by the peak detection algorithm. Slight differences between the ground truth and our peaks is a result of our method for labeling audio data. We discuss this in the next subsection.

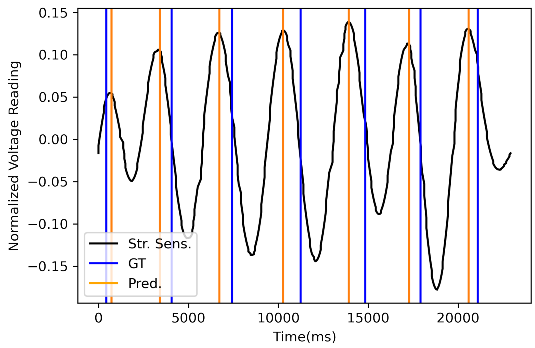


Figure 3: Standing Respiration Peak Comparison

Respiration Rate Ground Truth Labeling

Respiration audio was recorded while subjects wore Apollo. To label the ground truth data, initial timestamps for breath events were generated by first running a peak detection algorithm on the audio waveform with a minimum distance of D where D is the average number of data points between inhalation and exhalation. This distance is calculated manually through visual inspection of the audio signal. Since the audio sampling rate is 44000Hz, 1.5 seconds between inhalation and exhalation would result in a D of 66000. Visual inspection of the resulting plots, such as the one shown in Figure 4, were conducted to ensure no peaks were missed. For sections of audio data where external noise was an issue, manual labeling by listening to the audio was required. Since the study was conducted in a quiet environment, the highest peaks in the audio waveform usually resulted from respiration events.

The exact timestamp for the start of inhalation is not very important; what matters is that each inhalation event is recorded since the primary metric used by most related works concerning respiration detection is breaths per minute error (breaths PME). As a result, the label for an inhalation event is placed at the time where the inhalation produced the largest spike in the audio waveform (loudest point of inhalation).

Heart Rate Estimation

Heart rate estimation is more difficult than estimating respiration rate for multiple reasons. First,

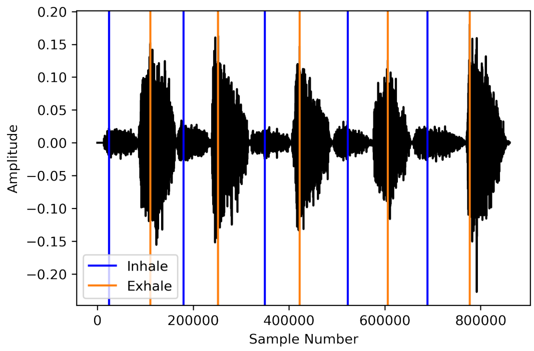


Figure 4: Automated Ground Truth Labeling for Respiration Rate

the force exerted on the pressure sensors from heart beat ballistic signals is significantly smaller than the force applied from expansion of the diaphragm. As such, noise introduced by small body movements or body position changing makes heart rate estimation difficult.

Respiration rate is slower than heart rate, and heart and respiration rate are directly correlated with one another.[30] As such, we can perform filtering to remove low frequencies by applying a highpass Butterworth filter to remove frequencies lower than 40breaths/minute (1.5Hz) which also happens to be the same as our minimum selected heart rate threshold of 40beats/minute. We can further decompose our original waveform by also applying a lowpass Butterworth filter to remove frequencies above our maximum heart rate threshold of 180beats/minute (0.33Hz). Figure 5 shows how the sensor data transforms during this process.

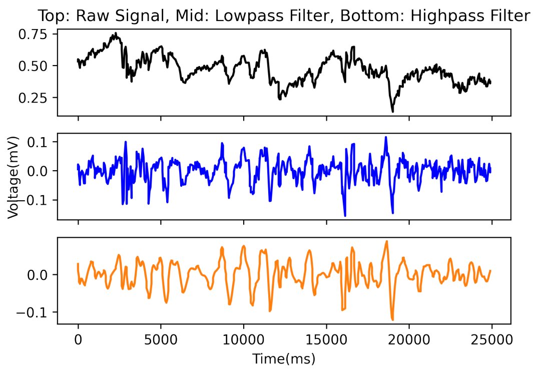


Figure 5: Sensor 1AC Transformed Using Lowpass and Highpass Filters

At this point, heart beat ballistic signals should appear as peaks. However, this method of data processing is susceptible to noises within the 0.33Hz-1.5Hz range, and not all peaks will be associated with heart beats. Small body movements can generate peaks in this frequency band as well. Ideally, we would apply machine learning to this task to extract the number of heart beats in a given time window. However, we lack both diversity of data (cannot prove that our models generalize) and enough data to train a model sufficiently. We discuss this problem more in-depth below. For now, we use an adaptive peak detection algorithm[28] with an adaptive window size determined by the dominant frequency in the heart rate range using FFT. We run FFT every 10 seconds to determine if the dominant frequency in the heart rate range changes. This adaptive windowing also helps reduce how noise affects our method because noise should be episodic.

Respiration Rate Ground Truth

The PH10 provides the ground truth data we will compare our heart rate estimations against. Figure 6 shows a plot of the raw ECG signal provided by the PH10. To label the heart beat ground truth, we first ran FFT on the raw ECG signal to extract the dominant frequency. Then, we used the peak detection algorithm provided by Python's SciPy module with a minimum distance set using this dominant frequency. A researcher manually verified plots of all PH10 data to ensure that all peaks were correctly found.

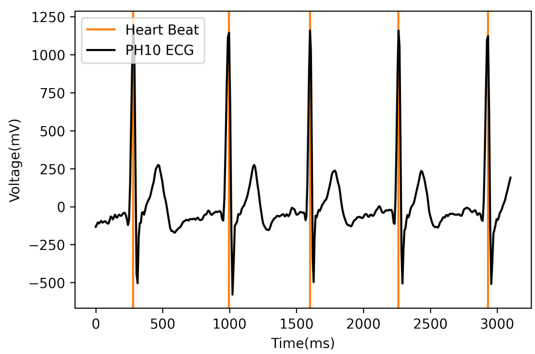


Figure 6: Automated Ground Truth Labeling for Heart Rate

Preliminary Evaluation

In this section, we describe our small user study and report the our initial results for Apollo.

User Study

We conducted a small user study with three subjects. Subject information is displayed in Table 1. Subjects were asked to wear the Apollo shirt whilst A. seated with their normal sitting posture in a chair, B. stand in place while every minute perform a 360° turn, and C. pace back and forth

Subject ID	Height	Sex	Shirt Size
S1	6’ 0”	M	XXL
S2	6’ 0”	M	L-XL
S3	6’ 1”	M	M-L

Table 1: User Study Demographics

down an empty hallway. Subjects were not told to hold still and were allowed to use their hands during the tests.

The walking test is included to determine the level of noise vibrations from the heel striking the floor will introduce into the sensor data. It stands to reason that these vibrations will primarily affect the pressure sensors as vibrations travel up the body. In all, we collected nearly 3.5 hours of data across all three subjects. Subjects 2 and 3 participated in the study for 15 minutes each, with the bulk of our data coming from subject 1.

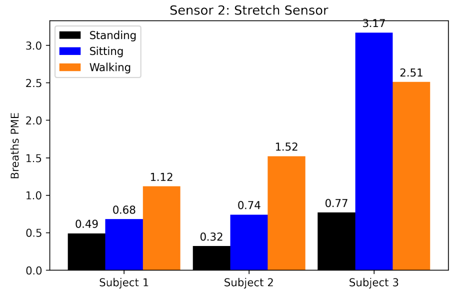
Impact of Covid-19: Covid-19 certainly impacted our ability to collect data both in terms of diversity of subjects and number of subjects. Remote data collection was attempted, but ultimately data collection needed to be done in-person to ensure data collection was successful for both Apollo and the ground truth sources. For in-person data collection, strict Covid-19 protocols were observed in accordance with our institutional review board protocol with William & Mary.

Respiration Evaluation

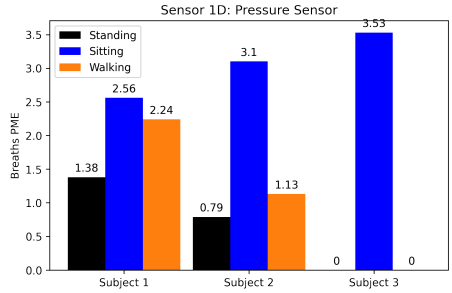
Breaths PME is the most commonly used metric in the ubiquitous computing community for evaluating systems measuring respiration rate. Any system with breaths PME <= 1 is considered highly accurate.

Figure 9 shows a breakdown of our resulting breaths PME by subject and by user study task. Unsurprisingly, some sensors performed better depending upon the body position of the user during a specific task. As shown in Figure 9a, Sensor 2 performs the best in the standing position. We discuss the high error for subject 3 below. The error for walking for subjects 1 and 2 is acceptable, and show promise that sensor 2 is capable of measuring respiration rate while a subject is not sedentary. Note: sensor 1B is not shown as there was an issue with the sensor for subjects 2 and 3 where the sensor reached the force saturation limit when users fully inhaled leading to a loss of data. This sensor is currently being modified to have a higher force saturation limit.

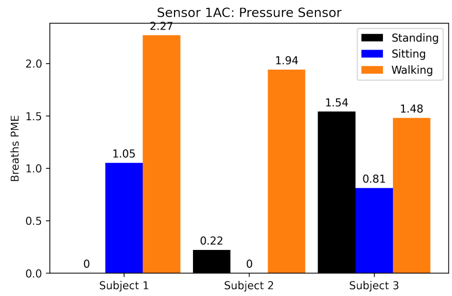
In Figure 9b, sensor 1D sees a sharp increase in error for the sitting position, likely due to the fact that the shoulder blades move forward when sitting so there is less tension of the compression material of the base shirt. Sensor 1D provided an



(a) Comparison of Error for Sensor 2



(b) Comparison of Error for Sensor 1D



(c) Comparison of Error for Sensor 1AC

Figure 7: Sensor Respiration Error by Subject and Task

exceptionally clear waveform when standing and walking for subject 3, and our filtering and peak detection method correctly captured each respiration event. The higher inaccuracy for subject 1 with sensor 1D can likely be attributed to the fact that subject 1 has a BMI of 39.1 meaning that the chest protruded outward creating an air gap between the chest and the pressure sensor.

In Figure 9c, sensor 1AC worked exceptionally well for the sitting position. We hypothesize that this is a result of 1AC being located at the bottom of the chest so sensor 1AC was able to maintain contact with the chest even when the compression material on the chest reduced pressure on sensor 1AC. However, sensor 1AC experienced higher inaccuracy during walking. We believe that this is a result of movement of the pectoral muscles as they experience vibrations during normal gait.

Sources of Error For Respiration Estimation: There are several possible sources of error that explain the differences in accuracy be-

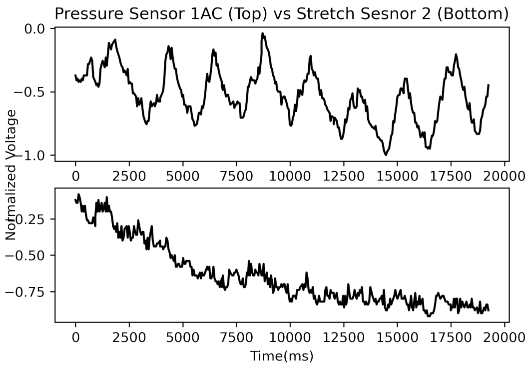


Figure 8: Subject 2: Sensor Comparison While Sitting

tween pressure sensors (1AC, 1D) and the stretch sensor (2). The most obvious sources of error are body posture, body measurements/shape, and body movement. We see a sharp increase in error for the stretch sensor for subject 3 when comparing standing respiration to sitting respiration. Subject 3 slouched while sitting which created slack in the stretch sensor. As a result, chest movement from respiration only minimally stretched this sensor. However, pressure sensor 1AC still remained in contact with the chest even while subject 3 slouched. Figure 8 shows the difference between data recorded for sensor 1AC and sensor 2 for a slice of time while subject 3 was sitting. As can be seen, the respiration waveform is significantly less noisy for sensor 1AC.

Body movement during walking can introduce noise as well. Stretch sensor 2 appears to be relatively resistant to body movement based upon only a slight increase in error for walking respiration detection for subject 1. However, exaggerated arm movement exhibited by subject 3 during walking introduce additional peaks in the data for sensor 2. When the arm swings, the shirt fabric is pulled which also pulls on sensor 2. A possible mitigation for this is to use a sleeveless compression shirt as the base shirt for Apollo instead of a short-sleeved compression shirt. With the arm no longer in a sleeve, arm movement should not pull on the chest area of the shirt as much.

As expected, body type changes the placement of the sensors on the body. A protruding chest vs a flat chest certainly changes how sensor 1D will contact the body which is why the error decreases as chest size decreases from subject 1 to subject 3 for standing and walking activities.

Heart Rate Evaluation

The results for heart rate estimation are not as encouraging as the results for respiration rate estimation. Several factors led to Apollo below state-of-the-art results for conductive textile based heart detection systems. We show our results and discuss possible sources of error with the hope that other researchers can avoid these problems in the future.

Sensor 2 extracted heart rate with an average of 4.88, 5.11, and 5.76 beats PME for subjects 1, 2, and 3, respectively. Error for this sensor increases sharply for sitting and walking tasks likely due to body posture and the natural movement of the body while walking.

Sensor 1D extracted heart rate for subject 1 with an error of 6.38 beats PME which rises sharply for walking likely due to large amounts of chest movement while walking. Sensor 1D surprisingly performed the best for subject 3. This appears to be an outlier and is not indicative that sensor 1D is accurate for estimating heart rate during walking

Sensor 1AC shows the most promise for extracting heart rate. The overall chest mass decreases from subject 1 to subject 3; with less tissue to absorb the vibration from the heart beat, sensor 1AC was able to estimate the heart rate of subject 3 with 0.96 beats PME while subject 3 was standing.

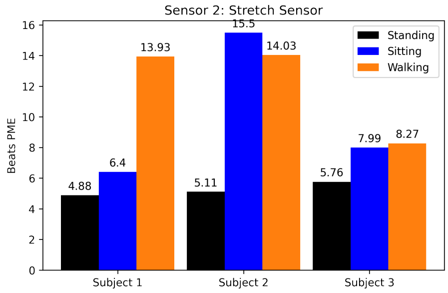
Sources of Error For Heart Rate Estimation:

It is clear that the conductive textile sensors have poorer accuracy for heart rate estimation when the wearer is not sedentary. Vibrations introduced from the heel striking the floor while walking, the arms swinging, and the chest twisting all appear to introduce considerable noise into the data recorded by each sensor. Posture definitely affects the accuracy of Apollo as well. Slouching reduces the amount of pressure the compression material uses to force the pressure patches to remain flush with the body of the wearer. As a result, the transmission of the heart beat ballistic force to the pressure patch is weaker.

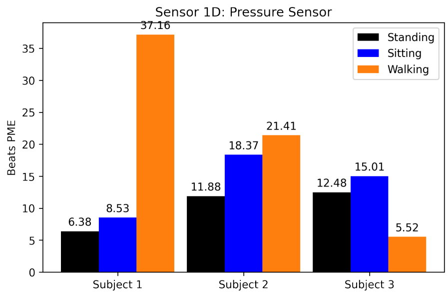
Discussion and Future Work

Improving Respiration Rate Estimation Accuracy

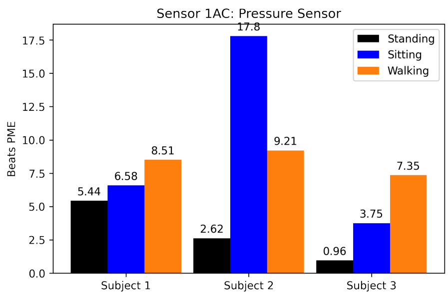
The peaks in the waveforms for each of the sensors resulting from respiration are significantly larger than the peaks resulting from heart ballistic signals; such a marked increase in peak size can be attributed to the larger forces exerted upon the sensors by diaphragm movement during breathing. As such, both the pressure sensors and stretch sensor achieved acceptable performance. We believe that further performance increases can be achieved by incorporating posture and overall body movement detection so that respiration rate is esti-



(a) Comparison of Error for Sensor 2



(b) Comparison of Error for Sensor 1D



(c) Comparison of Error for Sensor 1AC

Figure 9: Sensor Heart Rate Error by Subject and Task

mated using the sensor most accurate for that body position. Switching to a sleeveless compression shirt will also reduce noise created by arm movements. A stretch sensor run vertically down the latissimus dorsi muscle may also be beneficial since this muscle moves during respiration.

Improving Heart Rate Estimation Accuracy

The heart beat ballistic signal can be especially weak depending upon body type. Body types with large muscle or fat compositions around the chest and abdomen will most likely result in weaker signals since the heart beat signal must propagate through more tissue. Phyjama[19] determines heart beat from the least noisy pressure sensor which is usually the sensor the wearer is directly laying against. Coupled with the lack of movement during sleep, a much clearer heart beat signal can be detected. It is entirely possible that the compression shirt does not press our pressure sensors 1AC, 1B, and 1D against the skin enough to accurately read these signals. It may be necessary to switch to conductive textile patches that function as ECG sensors as mentioned in the related work section. The other option is to attach an adjustable strap to the base shirt to tighten over the pressure sensors though this would make the design more intrusive. We suspect that our pressure sensors would perform better for heart rate estimation if more pressure was used to ensure the sensors maintain contact with the chest.

Future Work

Work on Apollo is currently ongoing. With Covid-19 restrictions being modified or lifted, we plan to enroll more participants in our study. Additionally, we plan to conduct a separate user study with medium to high levels of activity including: climbing stairs, jogging, sprinting, and performing push-ups. The primary reasoning for such a user study is to evaluate the potential for Apollo to be used to monitor vital signs during exercise which could be useful for emergency detection for the elderly.

Machine learning continues to be an excellent way of extracting patterns from complex data. Convolutional neural networks (CNN) and recurrent neural networks (RNN) have repeatedly been show to be excellent choices for time-series data prediction tasks. We will test heart rate estimation using neural networks once our pool of subject data is sufficiently large.

We are in the fifth generation of Apollo design. We will continue updating the design as niche scenarios are encountered. Body temperature is another critical vital sign to monitor, and several recent works have experimented with fabrication of temperature sensitive conductive textiles.[13,21,25] We will attempt to integrate such fabrics into our design should they become commercially available.

Conclusion

In this paper, we presented Apollo, a wearable vital sign detection system using conductive textiles. Strategically placed fabric based pressure and stretch sensors sewn into a compression shirt can measure changes in the chest and abdomen associated with respiration and heart rate. Through a small user study, Apollo was capable of estimating respiration rate with a minimum error rate of 0 breaths PME and a maximum error of 3.53 breaths PME depending upon which sensor is used for respiration estimation. Apollo was capable of estimating heart with a minimum error rate of 0.96 beats PME, but the overall conclusion is that APOLLO struggled to estimate heart rate while the wearer moved or slouched. We touched on design faults and scenarios that contribute to inaccurate vital sign estimates, and we thoroughly discussed solutions to these issues.

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