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Breathing Monitoring from Chest-Mounted Sensor

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April 2025

A Report submitted in partial fulfilment

of the requirements for the degree of

BA(Mod) in Science in Computer Science

Trinity College Dublin
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Acknowledgements

I would like to thank my supervisor, Professor Declan O'Loughlin, for his patience, guidance, and encouragement throughout this project. His advice and insights motivated me to try out new strategies and significantly improve the quality of my work.

In addition to this, I am grateful for the support from my parents, Rajesh and Anita Patodi, whose motivation and support continuously pushed me to do my best.

Also, I want to express my gratitude to all of the faculty, staff, and students in the Department of Electronic and Electrical Engineering that I have had the pleasure of working with while attending Trinity College Dublin. Your support and encouragement have been invaluable to me along the way.

Contents

1 Abstract

Breathing is one of the things that we do every time without thinking, it reflects so much about our physical and mental state. Whether you are under stress, fatigue, illness, or just doing exercise, our breathing changes, and keeping track of that can be valuable. Traditional equipments used for measuring breathing rate are bulky, and that is not practical for everyday use. But this device provides a simpler and comfortable way to keep track of your breath.

This project focuses on the development of a compact, wearable system for real-time respiratory monitoring using a chest-mounted accelerometer. The system is built around the Arduino Nano 33 IoT, which has a 3-axis accelerometer and integrated Bluetooth Low Energy (BLE) for wireless data transfer. The primary objective was to capture and analyse chest motion and breathing under various breathing conditions. We started with the generation of artificial sinusoidal data to validate the algorithm's functionality in a noise-free environment. Once the algorithm was giving satisfactory results on that noise-free data, various forms of artificial noise were introduced to simulate real-world conditions such as vibrations, drift, and inconsistent breathing. In parallel, real data was collected across different breathing scenarios to assess the system's accuracy under different respiratory patterns. For this project, acceleration along the z-axis (inward and outward movement of the chest) was stored, then it was filtered using a combination of high-pass, low-pass, and moving average filters to isolate the breathing signal. A zero-crossing detection algorithm was then applied to estimate BPM and the start of each breath, while the peak detection method was also used as an alternative approach to calculate BPM. Manual stopwatch recordings were done with served as a reference dataset to verify the accuracy of the algorithm. Results indicate that the system reliably detects breathing patterns and provides accurate BPM estimation. Its low power consumption, wireless operation, and minimal hardware requirements make it suitable for continuous monitoring in both clinical and remote settings

2 Lay Abstract

In this project I aim to create a small, wearable device that can help us track breathing of a person by measuring their chest motion. A device named Arduino Nano 33 IOT which has a small sensor (accelerometer) in it, was placed on the chest to record the acceleration data and then it was wirelessly transferred to Computer using the Bluetooth. First, I created computer-generated (artificial data) to test whether the system is working properly for ideal scenario, then noise was added to simulate the real life breathing. This was done so that system can be tested before real data from participant under different types breathing ranging from slow, fast, deep and normal was collected. I used the method in which the acceleration was converted to velocity and when the velocity crosses x-axis, breaths were counted. At the time of recording real data, I used stopwatch to note the time of breath-in and breath-out, so that later it could be checked if the system is measuring accurately or not. This device can be helpful in hospitals or at home to monitor people's breathing in a simple and low-cost way.

3 Introduction

From the early 21st Century, wearable technology has changed the way we look at health tracking. From heart rate monitors to sleep trackers, these compact devices have made it easier than ever to collect data that was once limited to clinical settings[1]. But while some vital signs like heart rate and oxygen levels have been widely adopted in wearables, respiratory rate is still underused and often ignored in everyday health monitoring[2].

One of the main reasons for this is the way breathing is usually measured. Clinical tools like spirometers or plethysmographs are accurate, but they are costly and not built for comfort or long-term use. As of present, there are no good low-cost solutions out there that can monitor breathing passively, without interrupting daily life.

There is a noticeable gap in the way respiratory rate is monitored in current wearable medical technology served as motivation for this project. Although wearables have made significant progress in measuring heart rate and steps, but measuring respiratory signals accurately is still challenging, even though it could act as an indicator of general wellness. This challenge becomes even more relevant in post-pandemic life, where stress, sleep issues are on the rise, and people could benefit from continuous and passive breathing monitoring.

The goal was to develop a system independent of complicated architecture or large equipment. Rather, the objective was to figure out how to use a small inertial sensor, a technology that is well-known and easily accessible, to record something significant about our breathing. This project aims to create a portable solution that could be incorporated into fitness settings by concentrating on chest motion during typical breathing patterns. The simplicity of the hardware and data processing aligns directly with the objective i.e., to design a compact and practical tool for tracking breathing trends over time.

This problem is tried to be addressed in my work. This project visions to build a system that could track chest movement caused by breathing using a small inertial sensor, and process that data to estimate breathing rate, all without needing complex hardware. Rather than trying to match medical-grade precision, the aim was to find a balance between simplicity, usability, and decent accuracy. It is something that could be used in fitness tracking, remote wellness monitoring, or early screening tools.

The idea is based on the simple fact that our chest moves when we breathe: it expands as we inhale and contracts as we exhale. By placing an accelerometer on the chest, we can track this motion, and with proper filtering and analysis, we can figure out how many breaths a person takes over time. Although this method is not new in research, it is still evolving in how it is applied in real-world wearable devices for different uses.

4 Project Objectives

The goal of this project is to create and evaluate a wearable, basic system that uses chest motion to estimate a person's breathing rate. The focus was to keep the approach simple and useful, use only an onboard accelerometer and some basic signal processing techniques, instead of using intricate medical devices.

The main objectives of this project involve:

a) **Develop a wearable device that can accurately capture chest movement using inertial sensing:** This includes building a compact prototype using the Arduino Nano 33 IoT with its built-in accelerometer and enabling it to wirelessly transmit motion data to a computer for real-time analysis via Bluetooth. Continuous data acquisition should be possible, and the hardware should be small and unobtrusive.

b) **Design a signal processing pipeline to extract breathing patterns from raw motion data:** We will be integrating the raw acceleration data to get velocity, then applying filters to reduce drift and high frequency noise, and then extracting meaningful breathing waveforms. Two algorithms will be explored to estimate the breathing rate and then compared to get consistent results across different scenarios.

c) **Validate the system through data collection and reference comparison:** The recordings will be done multiple times for each scenario to capture sufficient data to apply primary analysis. The tests will include both natural and guided breathing conditions. Along with the test, a reference dataset using a stopwatch will be recorded, which later will serve as a reference or gold-standard dataset, used to verify the calculated results.

5 Literature Review

5.1 What is Breathing

Breathing is a continuous, life-sustaining process fundamental to human physiology. It involves inhalation (drawing air into the lungs) and exhalation (expelling it), where oxygen enters the bloodstream and carbon dioxide is removed. Though it occurs subconsciously, breathing is under both autonomic and voluntary control. It is regulated by the respiratory centers in the brainstem. This rhythmic cycle of breathing supports cellular respiration, ensuring that tissues receive adequate oxygen for metabolism.

Any deviation in this cycle, such as abnormal respiratory rate, depth, or pattern, can indicate a range of physiological disturbances, from respiratory illnesses to metabolic or cardiac dysfunctions [3]. Therefore, monitoring breathing is not only crucial for diagnosing diseases like asthma or sleep apnea but also for stress detection, athletic performance, and recovery tracking [4].

5.2 Biomechanics Behind Breathing

Breathing is a coordinated biomechanical process involving the dynamic interaction between the lungs, chest wall, diaphragm, intercostal muscles, pleural membranes, and the upper airway structures. The process works on pressure differences: during inhalation, the diaphragm contracts and descends, while the external intercostal muscles lift the rib cage, expanding thoracic volume and reducing intrapulmonary pressure, allowing air to enter the lungs. In quiet breathing, exhalation is passive and driven by elastic recoil of the lungs and thoracic cavity, but under exertion, abdominal and internal intercostal muscles contribute to forceful exhalation [5].

Breathing mechanics are not confined to the thorax. The upper airway (including the tongue, soft palate, and pharyngeal walls) plays a vital role in airflow regulation. As highlighted in [6], this region is biomechanically vulnerable due to its soft-tissue structure and lack of rigid support. Any disruption in this delicate balance can result in partial or complete airway collapse, as seen in Obstructive Sleep Apnea (OSA) [7].

Furthermore, breathing efficiency is directly impacted by lung volume and postural factors. While lying down positions increase upper airway collapsibility and decrease lung volume, upright postures improve diaphragmatic movement.

Two main types of Breathing Patterns as covered in [8]:

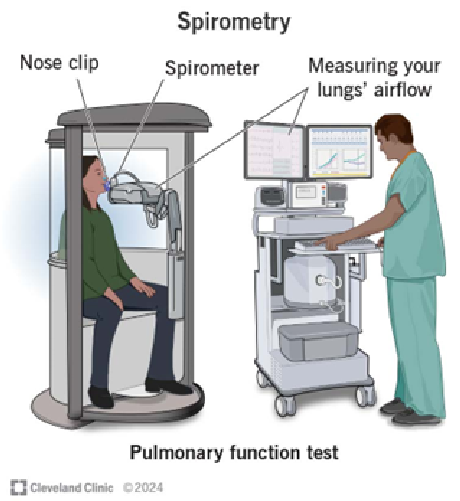
- **Thoracic (Chest) Breathing**: Involves lateral expansion of the chest wall; generally seen during stress, hyperventilation, or in individuals with diaphragmatic weakness.
- **Diaphragmatic (Abdominal) Breathing**: More efficient; involves downward movement of the diaphragm with minimal rib cage expansion, common in healthy individuals at rest.

In real-world settings, these patterns often overlap. However, respiratory illnesses like asthma, COPD, or restrictive lung diseases can shift breathing towards thoracic dominance due to reduced diaphragmatic mobility or airway resistance [5].

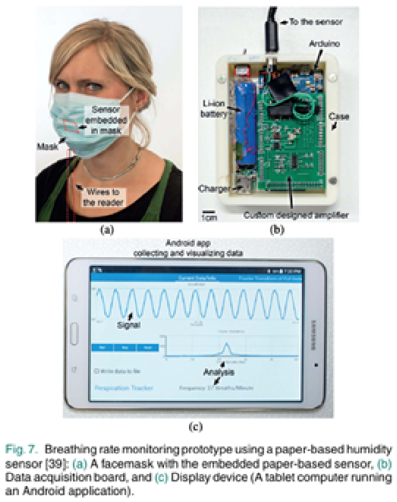
5.3 Conventional Techniques for Monitoring Breathing

Several clinical tools have been developed over the decades to measure breathing patterns. These include:

a) **Spirometry:** From the source [9]: A non-invasive pulmonary function test that measures the volume and flow of air during inhalation and exhalation, providing essential data on lung performance. Patients breathe into a spirometer, and healthcare providers assess lung capacity and airflow, aiding in the diagnosis and monitoring of respiratory conditions such as asthma, COPD, and cystic fibrosis. It also helps detect airway obstructions and monitors disease progression .



(a) using Spirometer



(b) using Humidity Sensor

Figure 1: Breathing Monitoring

b) **Capnography:** While spirometry measures airflow and lung volume, capnography monitors carbon dioxide (CO_2) concentration in exhaled breath. It produces a capnogram waveform that reflects ventilation efficiency and metabolic function. Capnography is especially useful in settings like emergency care and intensive care units and provides real-time, breath-by-breath analysis [10].

Other techniques include:

c) **Photolethysmography:** Uses chest/abdominal belts to detect volume changes that occurs with respiration [11]. These changes are reflected in PPG signal that allows us to extract respiratory rate information [12]. It provides accurate results but is restrictive.

d) **Humidity Sensors:** Since air exhaled has higher humidity than air inhaled, then breathing rate monitoring could be done using this method [4]. It needs to be placed close to mouth and nose which makes it bit uncomfortable.

e) **Lung Conductivity Sensing:** It uses bioimpedance changes in the thorax to monitor breathing. In this method impedance shift caused by air volume changes during respiration is detected. The authors of the paper [4] tested it on 10 adult subjects and got 100 percent accurate results.

5.4 No-Contact Measurement Techniques

a) **Infrared Thermography:** This method detects subtle temperature variations near the nostrils during the respiratory cycle. It tracks regions of interest (e.g., the nose) and uses signal processing techniques like low-pass filtering, autocorrelation, and pixel-based analysis to extract respiratory patterns. Depth or thermal cameras can be used to enhance tracking, making it especially useful for sleep studies[4]. The temperature difference during inhalation and exhalation depends on the geographical location. Also, it has a high computational cost and is sensitive to motion [13].

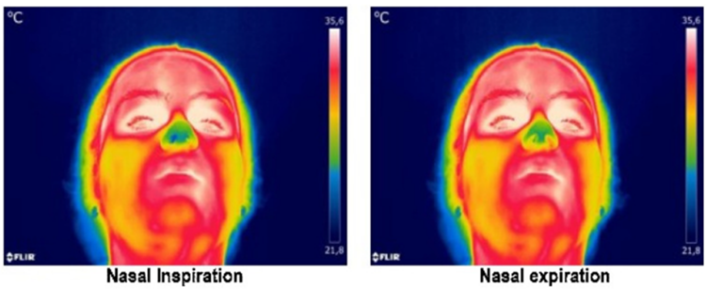


Figure 2: IR detection during inhale and exhale

Other methods include:

b) **Ultrasound-Based Monitoring:** Contactless ultrasound method provides comfortable and accurate respiratory monitoring. A 40 kHz self-injection-locked radar tracks chest and lung movement. The drawback of this method is that it is sensitive to movement, so changes in posture could distort the breathing signal[4].

c) **Laser Doppler Vibrometry (LDV):** Uses Doppler-shifted laser signals to detect chest motion. It offers high displacement resolution, but is costly and motion-sensitive [4].

5.5 Rise of Wearable Breathing Monitors

a) **Piezoelectric Transducers:** PVDF-based transducers are used in wearables to convert mechanical strain from chest movements into electrical signals. These signals are digitized and wirelessly transmitted via ultra-wideband (UWB) for real-time monitoring. While they are energy-efficient and lightweight, they require close contact with the body which may reduce comfort [4][5].

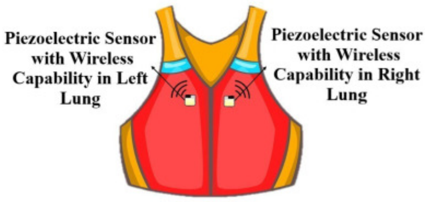


Figure 3: Picture depicting that the device can be placed in a jacket

Other systems include:

b) **Triboelectric Nanogenerators (TENG):** are devices that convert mechanical energy (e.g., chest movement) into electrical signals using the triboelectric effect, ideal for self-powered wearables as they can harvest their own energy. But their performance gets affected by environmental factors like humidity and temperature[14].

c) **Accelerometer-Based Systems:** Measure linear chest motion and often incorporate gyroscopes for enhanced accuracy [4]. This is talked-about in the next section.

5.6 Accelerometer-Based Breathing Monitoring

a) **Accelerometer Signal Processing:** Accelerometers are low-cost, compact sensors capable of tracking chest wall motion. When placed on the sternum or thorax, the Z-axis typically captures the vertical motion of breathing. Signal processing methods like zero-crossing detection, peak interval estimation, and bandpass filtering are used to extract respiratory signals. Studies show strong correlation between these readings and lab-grade systems such as spirometry or VICON motion capture [15][5][3].

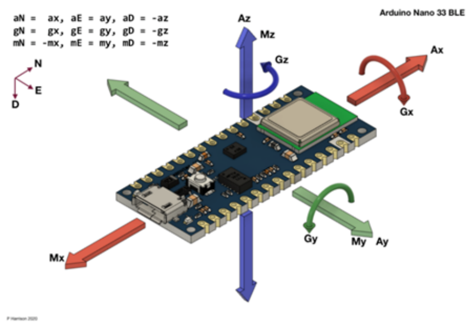


Figure 4: Arduino Nano 33 IOT with accelerometer sensor

b) **Sensor Fusion Techniques:** To reduce noise from general body motion, sensor fusion techniques like combining accelerometer data with gyroscope or magnetometer readings are used. Filtering algorithms like Independent Component Analysis (ICA) or Kalman filtering are employed to isolate breathing-related motion from other movement artifacts [5].

Other techniques include:

c) **Zero-Crossing Timing:** A method to calculate breathing rate by measuring the time between sequential zero crossings in the filtered signal.

d) **Mobile Connectivity:** Some systems transmit accelerometer data via Bluetooth for real-time monitoring and analysis on external devices.

5.7 Conclusion

Respiratory monitoring has evolved from clinical and manual tools to automated and wearable systems. Traditional methods like spirometry and capnography are accurate but impractical for continuous, non-intrusive use. Wearables offer promising alternatives through textile integration, flexible electronics, and inertial sensing.

Among these, accelerometer-based systems strike the best balance between cost, accuracy, and convenience. Especially when combined with intelligent signal processing and wireless transmission. These technologies are poised to redefine how respiratory health is monitored in daily life, remote care, and fitness applications.

6 Methodology

6.1 Introduction

We start with artificial data creation to confirm the feasibility of the algorithm in an ideal noise-free scenario. This was followed by the addition of artificial noise to simulate real-world conditions before conducting real data acquisition under controlled breathing scenarios. After successful validation, real data collection was carried out under four different controlled breathing scenarios to evaluate the effectiveness of the developed algorithm. The collected data was transferred wirelessly via Bluetooth Low Energy (BLE) module of Nano IOT to a computer for further processing. Then the signal goes through a couple of filters to highlight the required information of the data. The zero-crossing method was then applied to extract the breathing rate and other meaningful data, like the start of a breath.

One of the key reasons for choosing an accelerometer-based approach was its simplicity and ease of interpretation. The accelerometer provides clear data on chest movement after going through some filtering. Validating accelerometer output readings is also very easy, just by looking at the results in the direction of gravity, we can know if the accelerometer is working properly or not.

6.2 Hardware Implementation

6.2.1 Selection of Components

The primary hardware components used in this project was Arduino Nano 33 IoT, it was chosen due to its compact size and integrated BLE module, which enables wireless data transmission. It also has a Built-in LSM6DS3 Accelerometer (3-axis IMU) which provides an option to measure acceleration in X, Y and Z direction. In this project, the accelerometer was used to track the inward and outward movement of the chest while breathing.

6.2.2 Mounting the Sensor

The accelerometer was securely placed on the participant's chest, aligned with the natural axis of chest motion. It was secured tightly to minimize unwanted movement and ensure it stayed properly aligned with the chest's natural breathing direction. Data was collected primarily from the Z-axis (vertical movement of the chest). For this project, the acceleration in the other two axes(x and y), were ignored and not used in the calculation of BPM.

6.3 Artificial Data Creation and Noise Simulation

Before real-world data collection, artificial data was generated to test if the algorithm could accurately calculate Breaths Per Minute (BPM) under ideal conditions. This formed the foundation of the testing process.

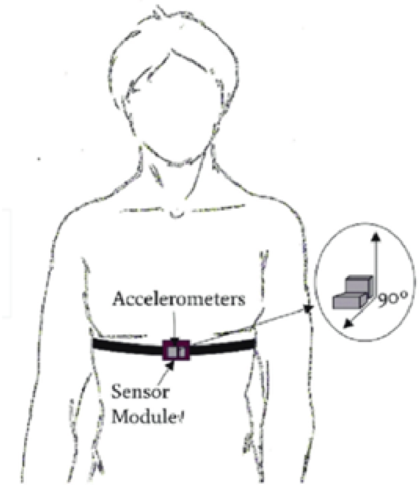


Figure 5: Device mounted on chest

6.3.1 Artificial Data without Noise

Initially, a pure sinusoidal wave was generated to represent an ideal breathing motion. The BPM was set at different values (e.g., 10 BPM, 15 BPM, 20 BPM) to confirm that the algorithm was working correctly. Since this data had no external noise, the goal was to ensure the zero-crossing detection method functioned correctly in an ideal scenario.

6.3.2 Adding Noise to Simulate Real-World Conditions

After validating the algorithm in an ideal setting, realistic noise was introduced to mimic real-world challenges:

- High-frequency noise to simulate small vibrations and sensor fluctuations
- Low-frequency drift to represent slow sensor bias changes over time
- Random amplitude variations to replicate inconsistent breathing patterns

This step-by-step noise addition allowed for fine-tuning the filter and signal-processing pipeline, ensuring robustness before proceeding to real data collection.

6.4 Real Data Acquisition

Once the algorithm was validated using artificial data, real data collection was conducted. The participant was asked to wear the accelerometer tightly against the chest while breathing under four controlled breathing scenarios. These scenarios were designed to observe how the algorithm performed under different breathing patterns, ensuring a robust BPM calculation across varied breathing styles.

6.4.1 Breathing Scenarios

a) **4-second breath with heavy breathing (2-second inhale, 2-second exhale)**: Deep breathing provided a clear and exaggerated breathing signal, making it easier to validate the zero-crossing detection method.

b) **4-second breath with normal breathing (2-second inhale, 2-second exhale)**: Similar to Scenario a, but with regular, relaxed breathing instead of forceful inhalation/exhalation. Helped test how well normal breathing patterns were detected compared to exaggerated deep breathing.

c) **Natural duration breath with heavy breathing**: The participant was instructed to breathe deeply but naturally, without following a strict time pattern. Allowed testing of the algorithm's ability to handle variability in breath duration.

d) **Complete normal breathing (Natural duration breath with normal breathing)**: This was the most realistic scenario, where the participant breathed naturally with no forced effort. It tested how well the system detected BPM in a completely uncontrolled real-world setting.

Each scenario lasted at least 30 seconds, allowing multiple breath cycles for analysis.

6.4.2 Reference Data Collection for Validation

To verify the accuracy of the breathing rate estimation, reference data was collected alongside the sensor recordings. While the accelerometer recorded chest motion, a stopwatch was used to log the start of each breath-in and breath-out manually. This recorded dataset, referred to as reference data, served as a ground truth for later comparison.

The purpose of collecting reference data was:

- To have a direct comparison between the algorithm's detected zero-crossings and the actual zero-crossings.
- To verify the algorithm's accuracy by ensuring that the estimated breath cycle timings match the recorded breath-in and breath-out timestamps.

This allowed me to confirm whether the algorithm was correctly identifying breathing cycles and estimating the breathing rate as expected.

6.5 Data Transfer from Arduino to Computer

For real-time data processing and monitoring, data was transferred wirelessly via BLE module. It eliminates the need for physical wiring, which allows the participant to breathe naturally without restrictions. BLE consumes low power, making it suitable for long-term data collection.

The sampling rate was set to a high value of 100 Hz. It was done intentionally as BLE drops data packets during transmission, which leads to data loss and missing values. So, by using a higher sampling rate than required, even if some packets are lost, the remaining data still provides an accurate representation of the chest motion. This ensures continuous monitoring without compromising accuracy.

6.6 Signal Processing and Filtering

Filtering is an essential step in processing accelerometer data to remove unwanted noise and extract the breathing motion signal accurately. The accelerometer captures both dynamic motion from breathing and static acceleration components, including drift and high-frequency noise, which must be filtered out to ensure reliable zero-crossing detection. The filtering approach used includes high-pass filtering, low-pass filtering, and moving average smoothing, ensuring a clean and interpretable signal.

6.6.1 Converting Acceleration

First, the raw acceleration (AccZ) is converted into velocity by integrating it over time.

6.6.2 Filtering Strategy

- **High-Pass Filter:** A high-pass filter (HPF) was applied to remove slow sensor drift and posture-related baseline shifts that can interfere with breathing signal detection. The sources of low-frequency drift include:
  1. Slow baseline shifts due to sensor bias.
  2. Gradual body movements, such as posture changes.
  3. Long-term signal drift, which can obscure zero-crossing points.
- **Low-Pass Filter:** A low-pass filter (LPF) was then applied to remove unwanted high-frequency noise from:
  i. High frequency vibrations from small muscle twitches
  ii. Sensor jitter
- **Moving Average:** A moving average filter was applied to smooth out small fluctuations in the velocity signal caused by noise left in the system even after going through High-Pass and Low-Pass filters.
- **Centering:** The velocity signal is then centered about the x-axis, so that it can be used in the next step to get the zero-crossing points.

6.6.3 Band-Pass Filter (Alternative Approach)

A bandpass filter could have been used instead of using both high pass and low pass filters separately. It was done as this provided more control and flexibility in tuning the filters and observing how different frequency components affected the breathing rate calculations.

6.7 Zero-Crossing Method for Breathing Rate Calculation

The Zero-Crossing method was the primary technique used to determine the breathing rate. This method detects when the velocity signal crosses the zero line, which could represent a complete breath cycle.

6.7.1 Working:

1. **Identify Zero Crossings:** The algorithm detects points where the velocity signal crosses the zero line. These points are the start of breath-in and breath-out and are stored as zero_crossing_points.
2. **Calculate Time Between Crossings:** The time difference between successive crossings is recorded. The average time between successive crossings is calculated and saved as avg_time.
3. **Compute BPM:** The breathing rate is then determined using:

   $$BPM = \frac{60}{2 \times \texttt{avg\_time}}$$

   There is one breath-in and one breath-out for one complete breath, which is why `avg_time` is multiplied by 2.

We used the zero-crossings method as the primary algorithm because it is simple, efficient, and computationally lightweight. It also works well with sinusoidal-like patterns, such as breathing signals.

6.7.2 Incorporating Hysteresis to Improve Accuracy

To avoid false zero-crossings due to noise, hysteresis was applied:

- A small dead zone of 1 second was introduced around the zero-crossing line to prevent minor fluctuations from being detected as actual zero crossings.
- This ensured that only strong, genuine zero-crossing points were counted, reducing false BPM readings.

6.8 Peak Detection Method

The peak detection method is used as an alternative to the zero-crossing method to estimate the breathing rate. Instead of tracking points where the velocity signal crosses zero, this method identifies local maxima (peaks) in the velocity signal, which correspond to the highest points of the breathing cycle.

The drawback of using the peak detection method is that it sometimes misses peaks if the breathing pattern is inconsistent.

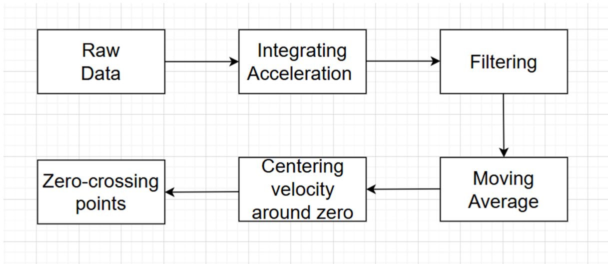


Figure 6: The flow showing how the raw data is being processed

7 Results

The results below present breathing rate estimation achieved using both zero-crossing and peak detection methods across multiple trials under different breathing conditions while the device was worn on the chest. All readings were recorded for approximately 30 seconds.

Scenario and Trial #	Ground Truth BPM by Stopwatch	Ground Truth # of ZC by Stopwatch	# of Zero Crossings	Avg Zero-Crossing Interval (s)	BPM by Zero-Crossing	BPM by Peak Detection
H4S 1	**14.7**	**15**	15	2	14.97	18.6
H4S 2	**-**	**-**	16	1.91	15.63	15.38
H4S 3	**-**	**-**	17	1.79	16.76	16.48
N4S 1	**-**	**-**	16	1.87	16.02	15.2
N4S 2	**-**	**-**	16	1.96	15.24	15.44
N4S 3	**-**	**-**	17	1.76	17.03	15.87
HND 1	**11.37**	**11**	21	1.45	20.58	20.42
HND 2	**13.05**	**13**	20	1.5	19.87	13.63
HND 3	**17.06**	**18**	18	1.72	17.37	16.62
CN 1	**14.52**	**15**	15	1.92	15.08	15.12
CN 2	**15.74**	**16**	17	1.84	16.26	15.93
CN 3	**16.28**	**17**	18	1.74	17.15	16.67

Table 1: Result table showing BPM, number of zero crossings, and average zero-crossing intervals for different breathing conditions.

Abbreviations: H4S = Heavy 4-Second Breathing, N4S = Natural 4-Second Breathing, HND = Heavy Natural Duration, CN = Complete Natural, BPM = Breaths Per Minute, ZC = Zero Crossing.

In Table 1, some values in the column of ground truth are missing. They were not measured using a stopwatch, as they are expected to be 15, because that was the requirement of the scenarios H4S and N4S.

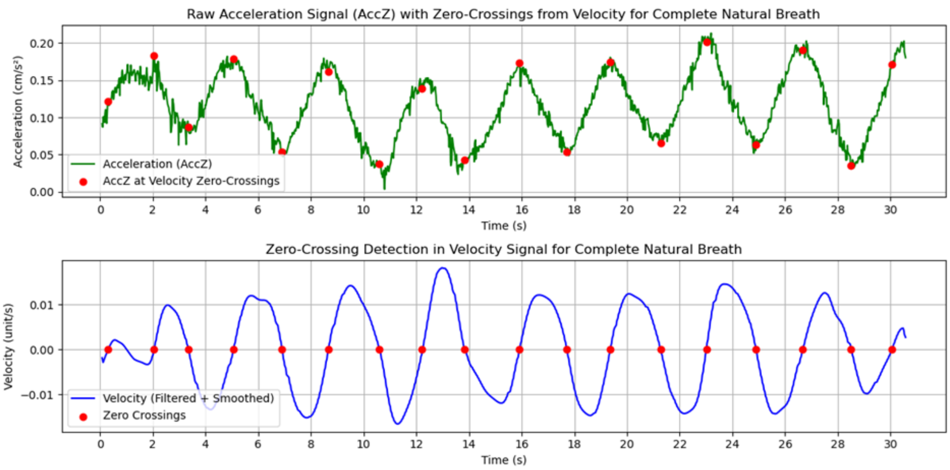


Figure 7: Overlay of ZCs on Acceleration Plot Demonstrating Match with Acceleration Peaks

8 Analysis

In this section, we will be analysing the chest motion data for all the scenarios, across three different recordings (Reading 1, Reading 2, and Reading 3) by comparing the raw acceleration (accZ) signals. Each recording will be represented by a distinct colour for clarity. We have marked by **X** symbol to indicate the zero-crossings of the velocity signal, which represent the exact moments when the direction of chest movement reverses, i.e., from inward to outward motion, and vice versa. These points are critical in identifying breathing cycles. The peaks and troughs in each waveform correspond to the moments of maximum chest expansion and contraction. These peaks and troughs will tell us about the depth of the breath.

8.1 Natural Breathing

We can see that all the readings are of duration 25 seconds to maintain consistency. All the plots in this scenario seem to be very consistent. There are 6 waves in each of the breathing, showing that the participants' breath was of the duration of about 4 seconds. For all the readings, there could be an extra zero-crossing at the very start, which is not caused by a real breathing event. It happens because velocity is zero at the beginning, and small fluctuations can cause it to immediately cross zero again. This zero-crossing should be ignored.

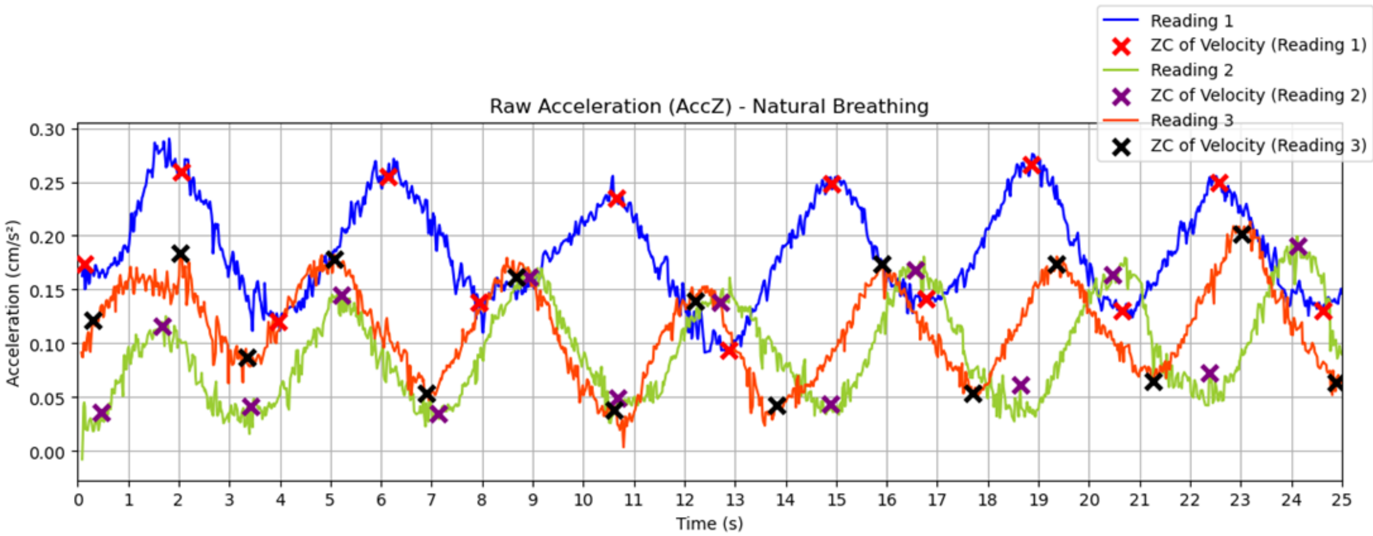


Figure 8: Complete Natural acceleration plots for analysis

Reading 1:

- The second zero-crossing (red) at 2 seconds is not perfectly aligned with the corresponding peak. However, the actual peak was observed about 300 milliseconds earlier. This might be due to breathing asymmetry.
- Another point to consider is the zero-crossing around 10.5 seconds. This zero-crossing doesn't coincide with the exact peak. This could be due to natural variation in the breathing rhythm, as we can see from the slope reaching this peak. It is smaller than the other slops. These subtle changes can cause velocity to cross zero-crossing earlier, even if the acceleration waveform is not fully there yet.

Reading 2:

- Overall, the zero-crossings in this reading align well with the breathing pattern.
- There are two exceptions, around 18.6 seconds and 22.5 seconds. These correspond to the last two breath-outs. This could be because during normal breathing, a person unintentionally holds their breath momentarily, which causes the velocity to linger near zero, resulting in multiple sign changes and shifting the zero-crossing.

Reading 3:

- Between 1 and 3 seconds, the waveform has an irregular shape. This could be due to some unwanted body movements (shift in posture) or physical adjustments of the device. This resulted in temporary distortion in the acceleration signal.
- After this brief irregularity, the waveform stabilized and displayed a consistent breathing pattern for the rest of the reading.
- Following the disturbance, the waveform becomes stable and reflects consistent breathing patterns for the rest of the reading.

8.2 Natural 4-Second Breathing

Here, the participant was asked to maintain a steady breathing cycle of 4 seconds (2 seconds inhale, 2 seconds exhale) while breathing naturally, without exaggerating the motion.

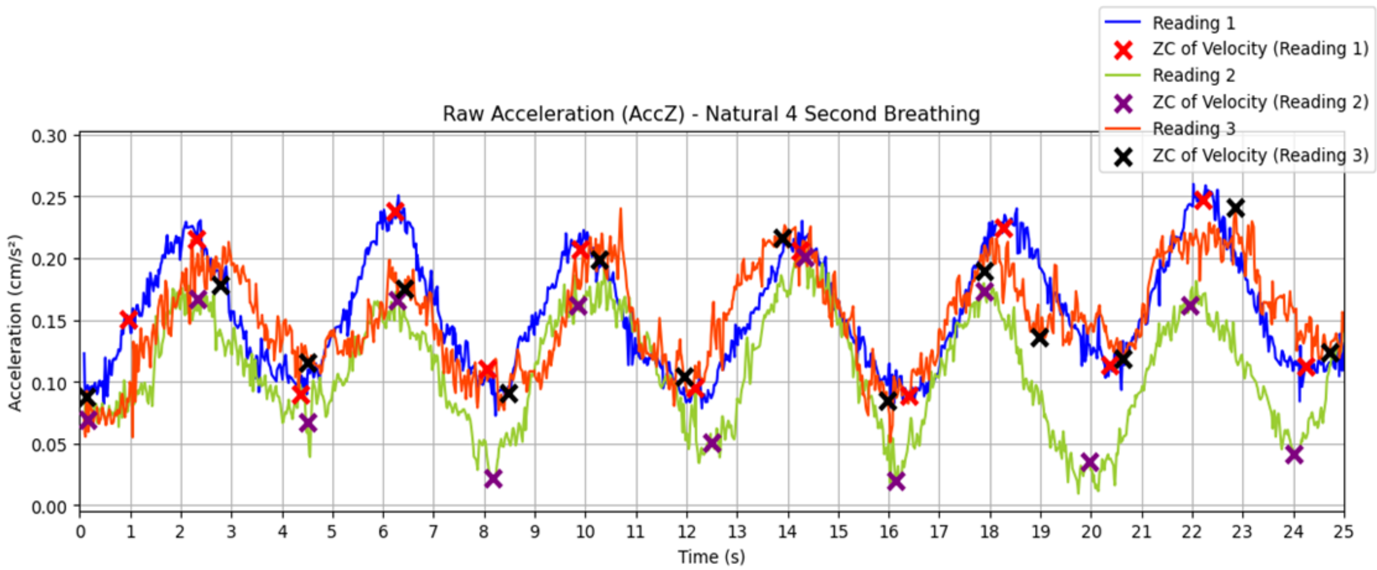


Figure 9: Natural breaths with 4-second duration breathing acceleration plots for analysis

Reading 1:

- A false zero-crossing appears at 1 second, likely due to initial body movement or filtering warm-up error. Filtering works best when it has enough data to process, but at the start, the sample size is small, resulting in some errors at the start.
- Another zero-crossing at 14.2 seconds occurs when the acceleration signal is still rising could be potentially a slightly shorter breath. It can be considered a natural breathing variation.

Reading 2:

- At 4.5 seconds, a sharp downward spike appears. This could be due to an abnormal event happening at that instant. It could be a cough, deep sigh, or a sudden and forceful exhale (least likely, as the participant was asked to breathe normally and naturally).
- At 9.9 seconds, noise introduces a false zero-crossing. At that time, in the waveform, we can see more noise than at any other time point. Because of this extra noise, zero-crossing was marked when the velocity crossed zero briefly.
- Around 20 seconds, there is a disruption in the breathing. The dip tells that chest expansion was reduced, meaning the participant might have hesitated mid-breath or gotten too relaxed towards the end of the recording.

Reading 3:

- At around 2.8 seconds, the zero-crossing appears to be in the middle of the upward slope. There are no visible peaks or reversal points nearby. From 1-3 seconds, this reading is showing unstable behaviour. It could have happened if the velocity had been hovering around zero during a low acceleration phase of breathing. But this zero-crossing could be counted as the real zero-crossing was close to this reading only. So, this would not cause great disturbance in the correct calculation.
- At 16 seconds, the zero-crossing occurs before the trough, which indicates mid-breath pause.
- At 19 seconds, a false crossing appears, likely triggered by noise between 18 and 21 seconds.
- We have seen that there are lots of errors in the reading 3, which means that the overall recording was not done in a good way. This could be due to the participant not following the given specifications properly, or some external disturbances coming from the surrounding environment.

8.3 Heavy 4-Second Breathing

In this scenario, the participant maintained a 4-second heavy breathing pattern (2 seconds inhale, 2 seconds exhale) with deeper breaths than in the natural condition.

Reading 1:

- A false zero-crossing occurs around 1.2 seconds as the velocity hovers close to zero.
- At around 7 seconds, a premature zero-crossing occurs about 100 milliseconds before the actual peak.

Reading 2:

- The signal is noisy and irregular, with large amplitude, which made zero-crossing detection vulnerable to false positives.
- A false zero-crossing just before 6 seconds occurs while the chest is still expanding. It could be caused by low acceleration and small noise, which made the velocity cross the zero momentarily.
- The zero-crossing at 14 seconds occurs slightly before the true acceleration peak — a minor but acceptable mismatch.

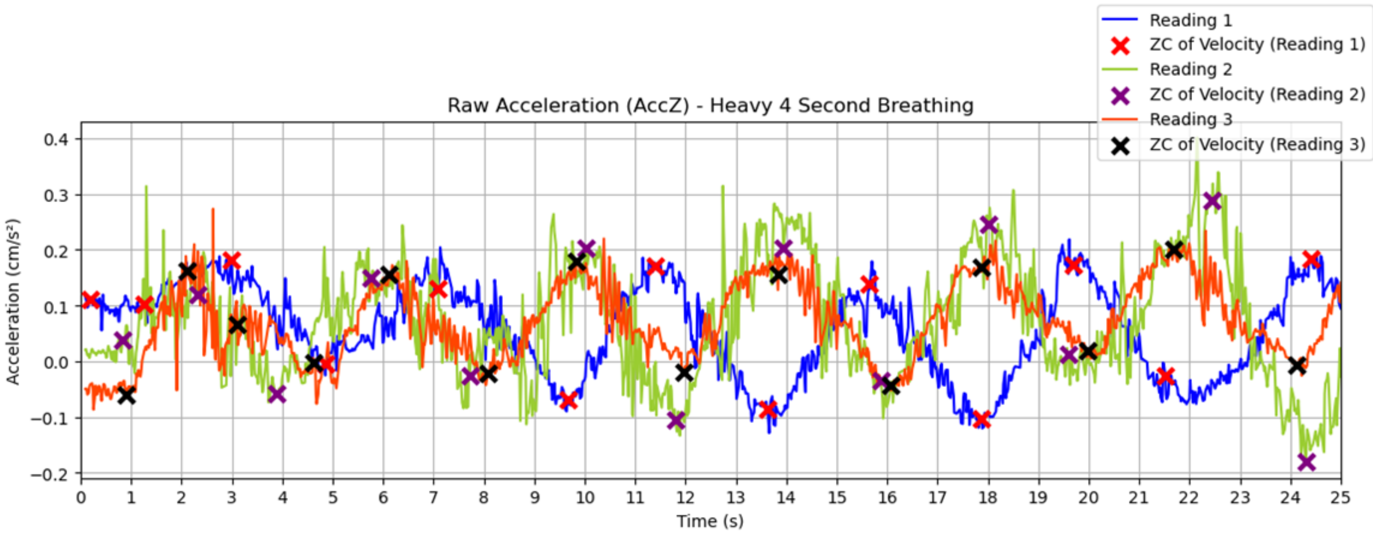


Figure 10: Heavy breaths with 4-second duration breathing acceleration plots for analysis

Reading 3:

- The signal is smoother. A false zero-crossing appears between 1.5–4 seconds, possibly due to external movement.
- Beyond that, the signal aligns well with breathing patterns.

8.4 Heavy Breathing with No Fixed Duration

In this scenario, the participant was asked to breathe heavily but naturally, without fixed timing between breaths.

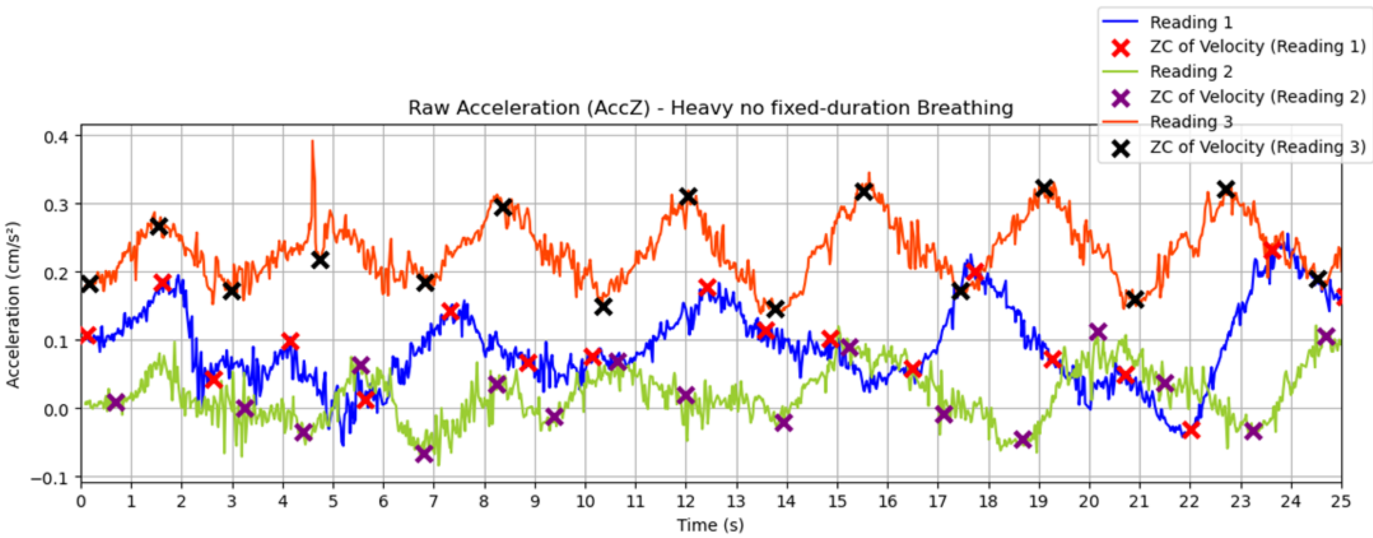


Figure 11: Heavy breaths for natural duration breathing acceleration plots for analysis

Reading 1:

- The waveform shows irregular rhythm, large amplitude variation, and the zero-crossings are not always centered at direction reversal points. The amplitude fluctuations here are very high compared to reading 2 and reading 3.
- The second zero-crossing at around 1.6 seconds is almost where it should be, but after that, there is a sudden drop in the acceleration, which most likely happened due to an abrupt change in the device placement.
- The zero-crossing at 5.7 seconds should have been at around 5.1 seconds, but it was not marked there, maybe because of the filtering we have done, which restricts two consecutive zero-crossings to be marked within the interval of 1 second.
- There were some disturbances in the waveform from 8-10.3 seconds. If there were fewer disturbances, then the correct zero-crossing would have been at around 9.2 seconds, and the zero-crossings marked at 8.8 and 10.1 would not be there.
- A similar thing happened at 13.4 seconds. If there were less noise, then we would have gotten the correct reading at 15.5, and there would be no zero-crossings at 13.5,14.9, and 16.5 seconds.
- At 20.6 seconds, a false zero-crossing occurred likely due to a brief breath-hold.
- Lots of extra zero-crossings were marked in this reading, which makes this reading one of the worst recordings.

Reading 2:

- Readings in waveform 2(green line) were relatively consistent with those in waveform 1. But still the algorithm missed some peaks here too.
- At 0.8 seconds, a false zero-crossing appears, which causes the real one at 1.5 seconds to be skipped.
- Noise between 2.5–3.5 seconds. It may be caused due to minor body movement.
- There is something different that happened from 10-14 seconds. From a look, someone can say that there is a false zero-crossing at 12 sec, but that would mean going from breath-in to breath-out took 3 seconds, although this could happen as the participant was asked to breath naturally in terms of breathing duration, but this does not match with the breathing the participant was doing before this. But when compared to the reference dataset of this reading, we came to know that the participant in mid-recording changed the breathing depth.

```
00:02.26 (Breath-in)
00:02.78 (Breath-out)
00:02.24 (Breath-in)
00:02.90 (Breath-out)
00:02.18 (Breath-in)
00:02.81 (Breath-out)
```

Figure 12: Reference dataset verification for anomaly

Reading 3:

- For this scenario of heavy and no fixed duration breathing, we got the most stable and consistent recording in reading 3(orange line).

- At 4.8 seconds, the zero-crossing was timed well, but the unusually high amplitude was likely due to sensor shift.
- Some noise appears between 4.5–7 seconds, but overall, the signal quality and detection are strong.

From the analysis above, we can say that the system works better when the person breaths naturally instead of breathing heavily. This contradicts our expectation from the section 6.4.1 (Breathing Scenarios). This happened because when the participant is asked to breath heavily, lots of noise and disturbance gets into the system because heavy breathing is not what we are used to.

9 Challenges and Limitations

While the overall system worked well and gave promising results, there were some obstacles I faced during development, testing, and data collection. They are mentioned below:

1. **Data Loss Over Bluetooth**
   The loss of data during Bluetooth transmission was the first problem I encountered. BLE is used by the Arduino Nano 33 IoT to wirelessly send data to a computer. However, BLE drops data packets during transmission, especially when there is interference or an excessively high transmission rate. I increased the sampling rate to 100 Hz, which means I sampled the data every 10 milliseconds, to minimise the effect of this. This meant that there would be sufficient samples to reliably extract the breathing pattern even if some data points were lost.

2. **Sensor Placement Sensitivity**
   To get consistent and correct readings, it is very important to place the sensor properly on the chest. If it is not placed tightly or not in the center, the quality of the signal drops. In the early testing, I was placing the sensor closer to the heart, which resulted in extra noise and incorrect BPM. The sensor needs to be properly aligned with the natural motion of the chest. Doing this is not always possible in real-world use, like if the person moves a lot.

3. **Real-World Noise and Movement**
   The system was tested while the participant was sitting still. So, if the person moves like walking, talking, or even shifting posture (which happened a lot), the accelerometer picks up that movement too. Since the signal processing pipeline is designed to detect even subtle breathing movements, these extra movements can introduce noise and reduce the overall accuracy of the system. To work on this, I added artificial noise in the artificial data to make it robust against that noise, but still the filtering needs to be more advanced.

4. **Manual Reference Logging**
   To create the reference dataset and validate the system's accuracy, I used a stopwatch by manually logging each breath. This did give a good baseline, but it isn't a perfect method. There is a delay of around 400 ms between you thinking to press a button and actually pressing it [16]. Human errors and timing delays (even by 500 ms) can make the reference not so great. To reduce this delay, I tried to log the lap around 300 ms before I actually should, which improved the reference dataset.

5. **Filter Tuning**
   Designing the filtering pipeline was a trial and error process. We had to find the right cutoff frequencies for the high-pass and low-pass filters, and it took time. For choosing the higher frequency, the signals were getting cut or distorted, and if the frequency was too low, then the noise wasn't removed properly.

6. **Limited Testing Scope**
   For the project, I had only two participants, which means that the system has not been validated across different body types, postures, and breathing styles. Features like body fat, lung capacity, and chest shape could affect the signal. For this project, testing with two people was enough to prove the concept.

7. **No Machine Learning or Adaptation**
   We used the zero-crossing method, which kept the system simple, but it also meant that the system could not adapt to irregular patterns or changes over time. Using a machine learning model could have potentially improved the accuracy in noisy environments. But choosing zero-crossing kept the algorithm lightweight and easily understandable.

10 Applications

The concept has genuine potential in a number of fields, even though it was created as a student prototype. In the fields of healthcare, fitness, and even stress management, a wearable device that can easily and comfortably measure breathing rate can be helpful. The following are some real-world applications for this type of system:

1. **Fitness and Wellness Tracking**
   Just like heart rate, breathing rate is a useful indicator of physical effort and recovery. This system could be used to monitor how breathing changes during exercise, at rest, or while sleeping. It helps users to understand their fitness level and endurance.
2. **Home Health Monitoring**
   For people with conditions like asthma, COPD, or sleep apnea, continuous breathing rate tracking could help spot early signs of trouble. With wireless data logging, the system could send alerts or trends to a phone. It may even send the alerts to a family member or a caregiver.
3. **Mental Health and Stress Detection**
   Breathing rate often changes with stress or anxiety. A wearable that tracks breathing could be used in stress tracking apps by providing feedback when breathing becomes shallow or irregular.
4. **Post-Surgery or Hospital Discharge Monitoring**
   Doctors frequently want to monitor vital signs when patients recover at home, especially after surgery or a respiratory condition. With this system, patients could be monitored remotely without requiring large, costly equipment.
5. **Academic and Research Use**
   Because the system is low-cost and customizable, it could be used in academic research projects studying sleep, exercise physiology, or respiration patterns in different environments.

11 Future Work

The current version of the project achieved its main goal, but there's scope for some improvement in both functionality and performance. Some ideas for future development include:

1. **Real-Time Processing**
   Right now, the processing and the analysis of the signal happen once we have collected the data. The next step would be to implement true real-time processing, either directly on the Arduino or on a connected mobile app.
2. **Multi-Sensor Integration**
   The current device works just by using an accelerometer. To improve accuracy during movement or in noisy environments, we could integrate additional sensors like a gyroscope or strain sensors.
3. **Mobile App Development**
   A dedicated app could be developed to display live breathing data, store historical records, and provide basic analytics. It could also alert the user if the breathing rate becomes too fast or too slow, just like a personal health assistant.
4. **Data Upload and Cloud Monitoring**
   For long-term use or clinical purposes, the system could upload data to a cloud platform where health professionals could access it remotely and monitor trends over time.
5. **Machine Learning for Pattern Recognition**
   The current system uses the method of zero-crossing. In future versions, I could explore machine learning models to detect more complex patterns, like shallow breathing, breath holds, or irregular rhythms.
6. **Improved Housing and Wearability**
   Right now, the sensor is simply held onto the chest, but in future versions, we could integrate the device directly into clothes (e.g., a smart shirt).

12 Conclusion

This project started with a simple question: Is it possible to track breathing accurately using just a small, wearable sensor? I wanted to build something lightweight, easy to use, and practical. After weeks of planning, building, testing, and tweaking, I can say that yes, it is possible. Though there are improvements possible, we can indeed measure respiratory patterns effectively.

Using the built-in accelerometer sensor on the Arduino Nano 33 IoT, I captured chest motion during breathing and estimated breathing rate in both controlled and natural conditions. The zero-crossing method, combined with a carefully designed filtering process, proved to be a reliable way to detect breathing cycles. Even though the setup was basic, and the hardware was minimal, the results were consistent.

Beyond the main outcome, the process itself was a significant learning experience. Challenges like noise handling, Bluetooth data drops, and sensor placement inconsistencies offered valuable insights into designing more resilient wearable systems. Artificial data generation helped validate the logic early on, while real-world data exposed the practical considerations of deployment.

Looking ahead, there are many exciting possibilities to work on that include real-time processing, integration with mobile platforms, enhanced wearability, and even the use of machine learning to identify complex breathing patterns. These improvements could elevate the system from a prototype to a fully deployable solution.

In this project, the user's privacy was ensured as no personal information was gathered or stored. The sole purpose of the device's design is to track the breathing patterns for research. The system was designed with user comfort kept in mind, and the device does not cause any physical harm to the user. The device should not be used for diagnostic purposes without the proper clinical supervision.

This project reflects how innovation does not always require complex systems. It is feasible to develop useful tools that significantly advance personal health monitoring by combining intelligent design with reasonably priced hardware. These kinds of solutions, which bridge the gap between research prototypes and practical applications, could lead to smarter, more inclusive healthcare as wearable technology develops further.

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