Towards Continuous Respiration Rate Detection While Walking

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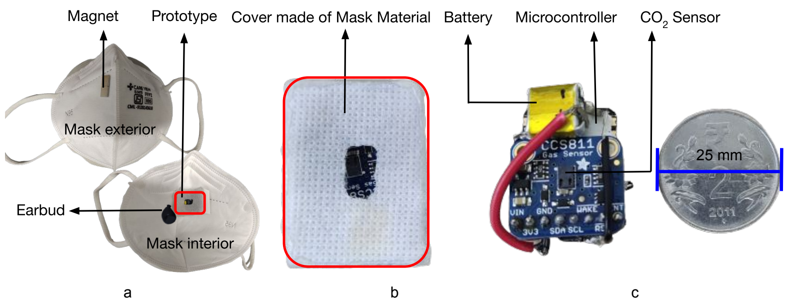

Fig. 1. (a) The sensing system along with wireless earbud (for ground truth collection), is fixed inside a mask using magnets. (b) The entire system is placed inside a 3D printed enclosure and is covered with mask fabric for the comfort of the wearer. (c) The system consists of a CO_2 sensor (CCS811) rigged with a microcontroller (SeedStudio Xiao nRF52840) and a battery.

Respiration rate is a vital sign to predict cardiac arrest, apnea, dyspnea and lung ailments. Past research has largely focused on sensing respiration rate in a controlled environment with participants at rest. But disease prognosis requires continuous everyday-life monitoring of respiration rate. In this work, we demonstrate how CO_2 sensor placed inside N95 mask can detect respiration rate during motion as well as rest with a better or comparable performance compared to previous work. Our system weighs 16 grams, runs uninterrupted for 2 hours, generalises across participants, does not require any learning algorithm and is reproducible.

Additional Key Words and Phrases: sensing; respiration rate; smart mask

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1 MOTIVATION AND APPROACH

Respiratory rate often measured as Breathing rate Per Minute (BrPM) is a number associated with the number of exhalations or inhalations in a minute. BrPM is a vital sign that should be monitored to predict Chronic Obstructive Pulmonary Disease (COPD), cardiac arrest, apnea and other clinical complications [6]. Previously different sensing modalities like Inertial Measurement Unit (IMU) [5] and audio [3] were used to monitor respiration rate but they do not perform well when the person is in motion. Moreover, algorithims designed to work in motion underperform when the person is in rest [5]. Research in continuous monitoring of BrPM during

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motion has been limited [8]. In this paper, we show how commercially available CO_2 sensor placed inside the N95 mask can be used to monitor continuous respiration rate, even under mild activity. Masks are ubiquitous and provide controlled environment [1, 2]. A person inhales O_2 and exhales CO_2. The N95 mask provides a shield to prevent the CO_2 from dispersing quickly into the air. The CO_2 concentration inside the mask increases with each exhalation and decreases with each inhalation. The periodic change in CO2 levels corresponds to respiration rate. During activity, like walking, the CO_2 concentration increases, but the periodic pattern stays similar. We apply Fourier Transform to capture the periodicity and extract the BrPM.

Hardware Reproducibility and Dataset: Our entire project is based on Commercial Off The Shelves (COTS) components. All the codes, data and data collection method are available in our Github repository[1].

2 EVALUATION AND RESULT

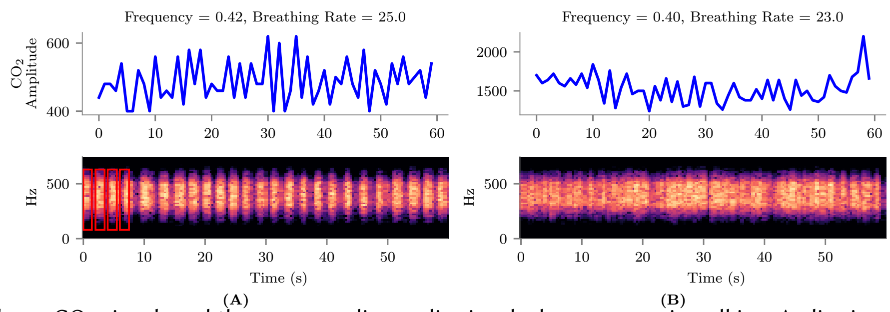

Fig. 2. Figure shows CO_2 signals and the corresponding audio signal when a person is walking. Audio signals cannot always be used to sense breathing when the person is walking. It is difficult to differentiate between exhalations and inhalations in the audio signal of **B** unlike in **A**. The first 4 exhalations of **A** are marked. CO_2 signal (top **A** and **B**) can sense breathing even when the person is walking.

We used the 6 Minute Walk Test (6 MWT) as a proxy for mild activity. We collected CO_2 data from 10 healthy participants in three conditions, **a)** when the person is sitting before the 6 MWT **b)** when the person is performing the 6 MWT and **c)** when the person is sitting after the 6 MWT. We used the CCS811 sensor to sense CO_2. The sensor was interfaced with a nRF52 based microcontroller (Figure 1 a). To collect ground truth data, we placed a wireless earbud inside the mask beside the CO_2 sensor to simultaneously record breathing audio. The spectrogram of each minute of recorded audio was manually labelled (Figure 2) for inhalation and exhalation cycles by two investigators. We fixed the sampling rate of the wireless earbud audio device to 1500 Hz to ensure that it does not record any speech and noise. The CO_2 data and the audio data was transferred over Bluetooth Low Energy (BLE) and Bluetooth 5 respectively to a laptop. Audio cannot be transferred via BLE due to its high sampling rate. We applied the Fast Fourier Transform (FFT) algorithm to each minute of CO_2 data. The fundamental frequency corresponds to the normal (eupnea) breathing rate per second. Respiratory rate has the range of 14-30 Breaths per Minute (BrPM) [5], therefore the fundamental frequency lies between 0.23-0.5 Hz. The CO_2 sensor had a sampling rate of 1 Hz. The highest breathing rate we can measure is 30 BrPM (0.5 Hz * 60 seconds).

The details of our data collection pipeline is in our Github repository. For each participant, we analyzed the signals collected during the 'Sitting', 'Walking' and 'Sitting after walking' phase. We segmented the audio and CO_2 data into 120 samples each of 1 minute duration. For each minute of data we extracted the respiration

[1] https://github.com/aryanvgithub/Smart-Mask-UbiComp2022.git

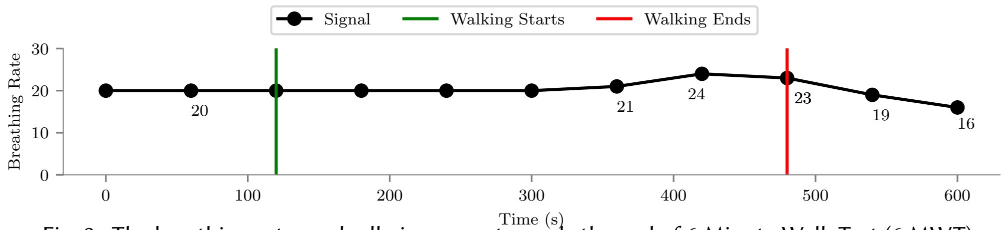

Fig. 3. The breathing rate gradually increases towards the end of 6 Minute Walk Test (6 MWT)

rate. Figure 2A shows the raw CO_2 recording for one of the participants when the person was doing a 6 MWT. Figure 2A (bottom) shows the corresponding audio spectrogram where the first four exhalations are annotated. There are 25 such exhalations. The fundamental frequency of the CO_2 signal is 0.42 which corresponds to 25 BrPM, meaning Mean Absolute Error (MAE) of 0. We repeated the same process for all the 120 samples and reported the MAE. Table 1 shows the results. Compared to previous work [5], our error is similar during 'walking' activity and is better during the 'sitting' activity. Our system generalises well for unseen participants since there is no learning algorithm involved. The CO_2 sensing system detects the increase in breathing rate over time as the person starts walking as seen in Figure 3. Abnormal increase in breathing rate during walking can be used as an early indicator of COPD and sleep apnea [6].

Challenges in annotation: Some audio samples could not be annotated due to absence of any distinct inhalation and exhalation pattern in its spectrogram. We did not use such samples for our evaluation. One such sample is shown in Figure 2B (bottom) which was recorded during the 6 MWT. It is important to note that even though the exhalations cannot be annotated visually or by hearing, the breathing rate can still be extracted from the corresponding CO_2 signal albeit without ground truth. A qualitative correctness of the CO_2 signal can be determined by comparing it with the preceding or the next sample where the ground truth audio was successfully annotated.

Activity	Mean (SD)	Range	Mean Absolute Error (MAE)
Sitting	15.40 (0.77)	13 - 17	0.067
During 6 MWT	24.17 (2.47)	16 - 29	1.785
Sitting after 6 MWT	19.80 (2.43)	14 - 24	1.375

Table 1. Activities along with the mean and range of respiratory rate (breaths/minute) and the error.

Inefficiency of metronome: Previous literatures [4, 7] have used metronome as ground truth for respiration rate. But, we observed (from audio and CO_2 data) that a 15 Beat Per Minute (BPM) metronome led to 13 exhalation or 13 BrPM for a participant, and thus metronome for ground truth collection is not advisable.

Energy Consumption: The CO_2 sensing system is powered by a small and light-weight 30 mAh Lithium Ion battery. It consumes 12 mA of current. The battery life can be improved in the future by duty cycling and by switching off unused peripherals in the microcontroller board.

Future Work: CO_2 data in combination with exhaled Oxygen data can be used to deduce a notion of fitness. We are currently investigating proxy sensing for inhaled oxygen.

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