AirCase: Earable Charging Case with Air Quality Monitoring and Soundscape Sonification

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ABSTRACT

Bad air quality and insufficient ventilation can have severe impacts on personal health. We present AirCase, a smart earable charging case that measures CO_2, volatile organic compounds, humidity, air pressure, temperature, and light intensity. The case powers both the air quality system and the earables. We also propose a model-driven air quality soundscape sonification strategy based on the audio capabilities of the earables. AirCase detects conditions unsuitable for measuring air quality (e.g., in pocket) in an office environment at 98.2 % accuracy with a simple classifier based on a single feature. We identified light intensity as the primary indicator to recognize occlusion. In contrast, the speed of the micro ventilator used to increase airflow inside the case did not offer any predictive value. In the future, we hope to see more researchers explore the hidden potential of the new platform.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile devices**.

KEYWORDS

earables; hearables; earphones; charging case; air quality monitoring; pollution

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1 INTRODUCTION

Earables have been heavily explored as a novel, ear-worn platform with personal tracking capabilities. Some examples are monitoring health-related parameters such as respiration [18] or brain activity [9]; or activity recognition to detect daytime activities [14] or eating episodes [4]. The platform also serves as the foundation of new interaction paradigms [25, 28]. In research, the focus, therefore, is on the device worn on the ear itself. State-of-the-art market-available earables are usually wireless and sold together with a charging case that contains much larger batteries compared to the earbuds[1]. Today, these charging cases are solely intended to provide power to the earables when the user is not wearing them, so they are recharged for the next use. However, as the user always carries the case with them, it creates an opportunity to implement additional sensors for mobile sensing. As the charging case may be placed, e.g., next to a person on the table, it seems particularly suitable for mobile environmental sensing scenarios.

To initially make the earable community aware of the hidden potential of the earable charging case and to spark novel ideas, we built a first prototype that follows the new paradigm. The charging case measures air quality and shares it back to the user by a soundscape sonification strategy. We conducted a data collection study in three different conditions (non-occluded + bright, non-occluded + dark, and occluded + dark) to gather 150 minutes of air quality data (30 x 5 minutes). Based on the collected data, we trained a simple classifier and performed 5-fold-cross-validation yielding 98.2 % overall accuracy.

In sum, our three main contributions are:

- an off-the-shelf charging cases with custom electronics to measure CO_2, volatile organic compounds (VOC), humidity, air pressure, temperature, and the light intensity, and which includes a micro ventilator for improved airflow in AirCase
- a model-based soundscape sonification strategy of air quality on earables
- an occlusion detection classifier to avoid measuring air quality when the device is, e.g., in the pocket

2 BACKGROUND AND RELATED WORK

Air quality and human life are closely coupled. For example, high humidity and temperature affect the level of human comfort [23] and high concentrations of VOC and CO_2 in the air even harm human health [10, 15]. Consequently, insufficient room ventilation rates in offices have severe adversarial effects such as higher rates of respiratory infections and overall more short-term sick leaves [22]. Therefore, personal mobile air quality measurement devices are expected to help the individual live a healthier life.

There have already been some mobile air quality monitoring devices in the field of ubiquitous computing. For example, *WearAir* [12] installed a VOC sensor and light-emitting diodes (LEDs) to a T-shirt. The LEDs indicate the air quality around the user measured by the VOC sensor, which informs people about the air quality

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[1] https://www.apple.com/airpods-pro/

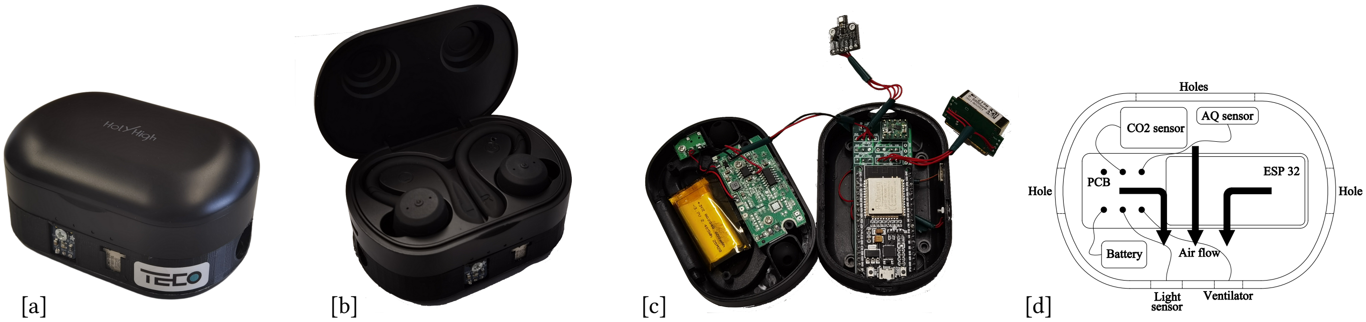

Figure 1: Different views of AirCase. [a] front side of the device showing the light sensor (left) and micro-ventilator (right); [b] open lid showing the earables placed inside the case for charging; [c] opened case showing the charging circuit (left) and custom PCB connected to sensors (right); [d] schematic drawing of the sensing tier.

straightforward. Jiang et al. [11] proposed a device equipped with CO_2, humidity, temperature, and light sensors, which can be attached on the backpack or clothes of the user. It performs indoor localization based on WiFi signals and can project the air quality onto the correct room. In addition to carrying sensor nodes directly on the human, there is also research focusing on vehicle-mounted air quality sensor nodes [3, 24]. The abundant space on vehicles generally leaves room for a larger number of more accurate sensors to be integrated than with wearables.

Related work in earable computing embedded environmental sensors directly inside the ear-worn device, but not for the primary purpose of air quality monitoring. E.g., to prevent heat strokes, temperature and humidity sensors inside earables can measure the body temperature, and evaporation of the wearer [7, 13]. Though air pressure sensors have been embedded inside earables, their sole purpose was to serve as an underlying sensing principle for interaction such as face gestures [1] or input by the muscles inside the ear directly [17].

To the best of our knowledge, no air quality sensors were embedded into earables or their related devices. Therefore, we proposed AirCase (Figure 1), an unobtrusive, augmented earphone charging case with air quality sensing for daily life.

3 AIRCASE

AirCase builds upon an off-the-shelf earbud charging case that we modified by adding custom electronics. Air quality sonification is presented to the user by the respective earables of the case. Occlusion detection relies on a simple machine learning classifier. Figure 2 gives an overview of the system components: in terms of information flow, multiple sensors are mounted to the MCU that runs an occlusion classifier. Measurements are then emitted via BLE to the mobile phone for recording and further processing, including sonification. From the aspect of energy flow, the battery of the charging case serves not only the earbuds but also the MCU and its sensors as well as the ventilation.

3.1 Hardware

Figure 1 shows the structure of AirCase. The foundation is the HolyHigh® earphones charging case (regular wireless Bluetooth earbuds with microphones and a push-button on each side, see Figure 1 [b]). A light sensor (SHARP® GA1A1S202WP) is installed on the front side of AirCase, aiming to detect the light intensity for the occlusion recognition. In addition, a ventilator (SUNON® UB393-500) is equipped next to the light sensor, which serves not only the occlusion recognition (measuring its rotation speed) but also the ventilation of AirCase, as the sensors located inside it must reflect the air quality of the surroundings. To improve ventilation, we have also designed holes on the back and sides of AirCase. To measure air quality, we placed an air quality sensor (BOSCH® BME680) to sense humidity, air pressure, temperature, and volatile organic compounds (VOC). As the BME680 only returns VOC as resistance, we obtain the indexed air quality (IAQ) using the Bosch Sensortec Environmental Cluster (BSEC) library based on VOC and takes temperature and humidity into account. This allows us to assign VOC air quality based on the reference IAQ values provided by Bosch. In addition, we added a CO_2 sensor (WINSEN® MH-Z19B). We utilized the battery of the charging case as the power supply of the aforementioned sensors and the micro-controller unit (MCU), an ESP32. The firmware is written in Arduino. For easier assembly, we designed a custom ESP32-based printed circuit board (PCB) that sits tightly in the case and simplifies cable management (see Figure 1 [c], right). The rough overhead of AirCase is listed

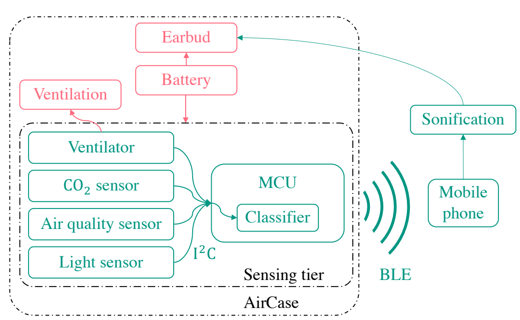

Figure 2: Frame of AirCase system. Red parts present the energy flow and green parts indicate the information flow.

in Table 1. We remove the screws from the case and 3D-print a new bottom lid which is slightly thicker to account for the space required for the sensors. To emit, record, and analyze the acquired signals, we developed an Android application to communicate with the ESP32 via Bluetooth Low Energy (BLE). The measurements are sampled and sent every five seconds (0.2 Hz). Figure 1 [d] shows the schematic drawing of AirCase.

In the extreme case, i.e. with all sensors active and constantly sending data via Bluetooth, the AirCase can operate continuously for 5 hours. Thanks to the occlusion detection (see subsection 3.3), the AirCase will run for more than 5 hours, depending on the state the AirCase is in, as the MCU stops collecting and sending data to a certain extent in occlusion.

Table 1: System overhead.

Hardware	**Cost**
Earbud + charging case	40 €
Light sensor	3 €
Ventilator	15 €
Air quality sensor	15 €
CO_2 sensor	25 €
Customized PCB	1 €
Summation	99 €

3.2 Soundscape Sonification Strategy

Earables offer a design space for rich and immersive soundscape experiences. Sonification, on the other hand, describes the transformation of data to sound. In AirCase, we designed a two-tiered soundscape sonification strategy: a background tier, indicating temperature as well as humidity referring to human comfort and an alerting tier to inform the user about potentially harmful air quality with respect to the level of VOC (measured as IAQ) and CO_2.

Background Tier. To combine humidity and temperature into a single measure, we defined the *modified temperature* T_m as proposed by Steadman [21]:

$$T_m = 1.07T + 0.2e - 2.7\,,$$

where T indicates the measured temperature and

$$e = 6.105\frac{H}{100}\exp\left(\frac{17.27T}{237.27+T}\right)$$

with H denoting the humidity. Based on a study by Tanabe and Kimura [23], we define the *neutral temperature* T_n with respect to the modified temperature by averaging the neutral temperature for different groups of users as:

$$T_n = 25.7^{\circ}C\,.$$

We use the absolute difference between T_m and T_n to control the volume of the music playing on the earables. The greater the absolute difference is, the higher the volume is.

Alerting Tier. The alerting tier informs the user about deviations in air quality that have a significant impact on human health, i.e., VOC and CO_2. The alarm starts when CO_2 value exceeds 1000 ppm [10] or VOC values above 100 IAQ (described as "little bad air quality" by the manufacturer of the VOC sensor [6]). The higher the level of CO_2 and VOC are, the higher the volume of the alerts will be.

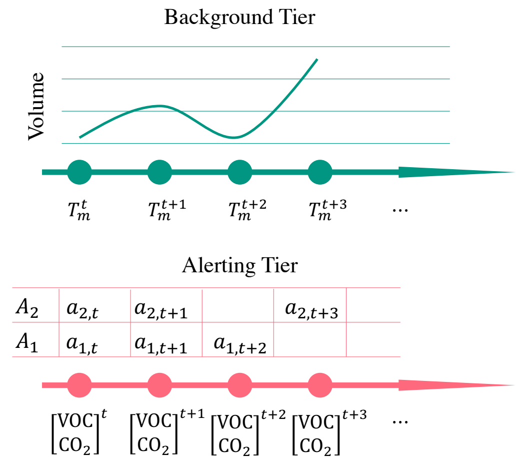

Figure 3: Sonification model of AirCase. Background tier gives the user feedback about comfort and the alerting tier warns the user about potentially harmful air quality.

Sonification Model. Wolf et al. [26] proposed a model for data-driven sonification using soundscapes that we apply to our use case. Figure 3 shows our approach. For the background tier, the volume of background music changes according to changes of the modified temperature at each time step. For the alerting tier, VOC and CO_2 activate the respective alerts (i.e., A_1 and A_2). $a_{i,t}$ denote the alarm in group A_i at time step t. In our implementation, we choose t as one minute and apply a heavy breathing and coughing sound to warn about CO2 and VOC levels, respectively. The user can choose background music according to their preferences as we manipulate the system settings directly.

3.3 Occlusion Recognition

When AirCase is occluded (e.g., while in the bag or pocket of the wearer), the readings of the sensors are not informative as they do not reflect the air quality of the surroundings. Keeping the measurements active under such conditions is also a waste of energy. The main differences between occlusion and an open environment are light and ventilation, as the occlusion blocks the light and impedes the airflow. Thus, we were interested to realize occlusion recognition based on the measurements of light intensity and rotation speed of the ventilator, which we initially explored in our paper.

Dataset. We collected 150 minutes overall in 15 occluded and 15 non-occluded conditions at our lab (5 minutes recording each). Occlusions include placing AirCase in pockets (N=5), bags (N=5), and cabinets (N=5) of five different users. We sampled data at ten different rooms at different times (1 / 3 at night and 2 / 3 during the day) to change light settings. As we want to evaluate occlusion more robustly on a per-minute basis, we applied a one-minute sliding window on every 5-minute recording (step size 5 seconds).

Feature Extraction. Before classifying the samples, we performed automated feature extraction with *tsfresh*. We apply it to the light intensity and ventilator speed time series (each series lasts 1 minute) and filter out the most relevant features associated with labels based on the false discovery rate [5]. This resulted in no relevant features based on the speed of the ventilator. This was also confirmed by training classifiers on the features of the ventilator that did no perform better than random (see Table 2). Looking at the remaining

Table 2: Occlusion detection using ventilator speed.

Classifier	Precision	Recall	F1	Accuracy
SVM	71.7%	99.6%	83.4%	81.2%
Neural Network	69.0%	89.0%	78.0%	75.0%
Random Forest	69.0%	7.4%	13.4%	51.5%

features quickly revealed that the absolute light intensity is the sole predictor of occlusion in our dataset. The feature that represented this best was the absolute sum of light intensity of the sample. Figure 4 [a] shows the logarithmic of s_l denoting the sum of light intensity in sliding windows of all recordings, while [b] shows the logarithmic of s_v, the sum values of ventilator speed in sliding windows. It can be well observed that the light is distinctive to predict the occluded and non-occluded conditions, whereas the ventilator speed does not change consistently across them.

Threshold Classifier. To avoid having to select the optimal threshold by hand, we fit a support vector machine classifier (SVM) using *sklearn*. We perform 5-fold-cross-validation and avoid that samples from the same recording are in the training and validation set at the same time using three different classifiers i.e. SVM, neural network, and random forest. After training and validation, we acquire the result described in Table 3.

Results. From Table 3 we find that a SVM achieves an acceptable classification accuracy in our office environment for occlusion detection using the light sensor measurements solely. Therefore, we can turn off the sensors to save energy when the device is occluded. As the ventilator's speed does not improve occlusion recognition, we can also shut it down.

Table 3: Performance of the AirCase occlusion detection.

Classifier	Precision	Recall	F1	Accuracy
SVM	96.8%	100%	98.4%	98.2%
Neural Network	91.0%	100%	95.3%	95.0%
Random Forest	98.5%	69.2%	81.3%	84.4%

4 DISCUSSION

We have demonstrated how an earable charging case can be equipped with air quality sensing, introduced a soundscape sonification strategy, and preliminary showed the possibility to detect occlusions.

4.1 Limitations

Currently, we only evaluated the occlusion detection of AirCase on a limited set of data samples acquired from the same building. It remains to be investigated how well AirCase works under real-life settings. For example, additional sensors such as a light spectrum sensor may be required. Possibly, the user could define this threshold for occlusion detection based on personal preference, or AirCase could activate depending on the current activity of the user (e.g., detecting where the device is carried [2]).

Our sonification strategy remains to be evaluated with the users.

Also, we would like to emphasize that AirCase is currently much larger than necessary. The BME680 and GA1A1S202WP sensors both only have a footprint of $\leq 3 \times 3 \times 1\ mm^3$ (l × w × h). Therefore, they could be well integrated directly onto the charging case's printed circuit board.

4.2 Air Quality Feedback

At the moment, information about air quality is presented as raw values inside the app or based on our sonification strategy that remains to be evaluated with the user. Another feedback mechanism could present air quality through light directly on the earable that makes the surrounding people in public spaces aware of the information obtained by the case [8]. Of course, the case could also show the air quality directly.

4.3 Smart Charging Cases

Beyond the smart earable charging case with air quality monitoring presented in our paper, we share three other possible research and application paths.

Health Tracking. Compared to a phone, an earable charging case may be kept inside the pocket during usage. Therefore, it could serve as a better sensing platform for continuous health-related parameter tracking. For example, it could predict the energy expenditure and count the steps of the user, as the hip location proved to be most reliable in past work [19]. Also, the surface area of the charging case presents opportunities for sensors. A handheld Electrocardiography measuring device could place its conductive metal electrodes on the outside of the case (e.g., similar to *AliveCor Kardia Mobile*).

Subtle Gestures. Subtle interaction that requires low effort and can be hidden from others continues to receive attention in HCI research and was recently systematically investigated [16]. We imagine that a smart charging case carried in the pocket could be an enabler of such hidden interactions. For example, Saponas et al. [20] and Wu et al. [27] presented pocket-based input based on textile sensors. Capacitive sensors embedded on the outside of a charging case could allow similar interactions.

Item Tracking. Wu et al. [27] introduced a method to recognize objects placed inside the pocket of the user (e.g., earbuds charging case). Similarly, the charging case itself could be equipped with sensors to make it aware of other items inside the pocket. The case could then remind the user about forgotten objects.

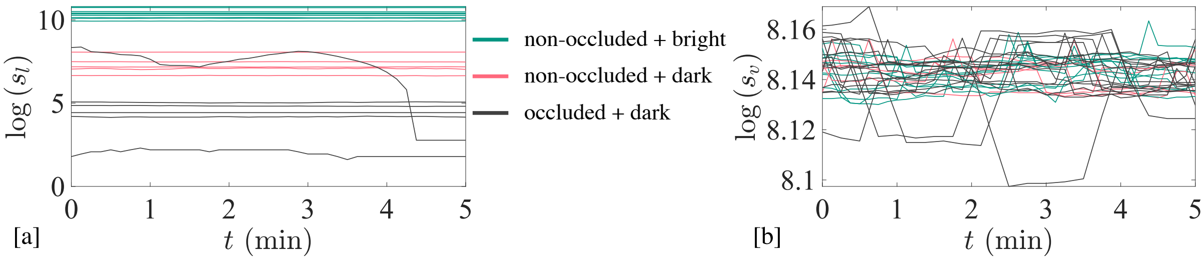

Figure 4: Logarithmic sum of values in sliding windows. [a] logarithmic sum values of light intensity, [b] logarithmic sum values of ventilator speed.

5 CONCLUSION

Earable charging cases offer space and large amounts of power for new types of use cases. We explored the potential of the new platform as an unobtrusive mobile air quality sensor station for daily usage. AirCase builds upon a simple threshold-based approach by measuring light intensity to detect occlusions of the case. The speed of the micro-ventilator as an indirect measure of airflow did not have any predictive value. Additionally, AirCase uses the earables' audio capabilities to inform the wearer about air quality based on a model-driven soundscape sonification strategy.

Future Work. We are interested in looking at other strategies for occlusion detection. Moreover, we are looking forward to other work that makes use of the earable charging case as a sensory platform.

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