Nanotechnology and Precision Engineering

Breath monitoring, sleep disorder detection, and tracking using thin-film acoustic waves and open-source electronics

Cite as: Nanotechnol. Precis. Eng. **5**, 033002 (2022); https://doi.org/10.1063/10.0013471
Submitted: 10 May 2022 • Accepted: 27 July 2022 • Published Online: 18 August 2022

Jethro Vernon, Pep Canyelles-Pericas, Hamdi Torun, et al.

Nanotechnology and Precision Engineering | ARTICLE | scitation.org/journal/npe

Breath monitoring, sleep disorder detection, and tracking using thin-film acoustic waves and open-source electronics

Cite as: Nano. Prec. Eng. 5, 033002 (2022); doi: 10.1063/10.0013471
Submitted: 10 May 2022 • Accepted: 27 July 2022 •
Published Online: 18 August 2022

View Online Export Citation CrossMark

Jethro Vernon,[1] Pep Canyelles-Pericas,[2] Hamdi Torun,[1] Richard Binns,[1] Wai Pang Ng,[1] Qiang Wu,[1] and Yong-Qing Fu[1,a)]

AFFILIATIONS

[1] Faculty of Engineering and Environment, University of Northumbria, Newcastle upon Tyne NE1 8ST, United Kingdom
[2] Department of Integrated Devices and Systems, MESA+ Institute for Nanotechnology, University of Twente, Enschede 7522 NB, The Netherlands

[a)] Author to whom correspondence should be addressed: Richard.fu@northumbria.ac.uk

ABSTRACT

Apnoea, a major sleep disorder, affects many adults and causes several issues, such as fatigue, high blood pressure, liver conditions, increased risk of type II diabetes, and heart problems. Therefore, advanced monitoring and diagnosing tools of apnoea disorders are needed to facilitate better treatment, with advantages such as accuracy, comfort of use, cost effectiveness, and embedded computation capabilities to recognise, store, process, and transmit time series data. In this work we present an adaptation of our apnoea-Pi open-source surface acoustic wave (SAW) platform (Apnoea-Pi) to monitor and recognise apnoea in patients. The platform is based on a thin-film SAW device using bimorph ZnO and Al structures, including those fabricated as Al foils or plates, to achieve breath tracking based on humidity and temperature changes. We applied open-source electronics and provided embedded computing characteristics for signal processing, data recognition, storage, and transmission of breath signals. We show that the thin-film SAW device out-performed standard and off-the-shelf capacitive electronic sensors in terms of their response and accuracy for human breath-tracking purposes. This in combination with embedded electronics makes a suitable platform for human breath monitoring and sleep disorder recognition.

KEYWORDS

Surface acoustic waves, Sleep disorder, Apnoea, Open-source electronics, Pattern recognition, Piezoelectric thin film

I. INTRODUCTION

Sleep disorders are frequently observed in adults, having a profound impact on the health and quality of life of patients. There are six major sleep disorders: insomnia, circadian rhythm disorders, sleep-disordered breathing, hypersomnia/narcolepsy, parasomnias, and restless legs syndrome/periodic limb movement disorder. Among those, apnoea sleep-disordered breathing is considered a serious medical condition due to the risk of sudden death and the reduction of life expectancy.[1]

Sleep apnoea is a primary sleep disorder consisting of abnormal breathing and pauses during sleep. There are three categories of sleep apnoea: obstructive sleep apnoea, central sleep apnoea, and complex sleep apnoea.[2] Obstructive sleep apnoea stops breathing for at least ten seconds, collapsing the upper respiratory system. In contrast, in central sleep apnoea, the interruption of airflow happens when there is not an effort to breathe, commonly due to brain miscommunication with the muscles that control breathing. Some patients have a combination of all the above apnoea, resulting in a complex sleep apnoea.[2] In such cases, monitoring and diagnosis are challenging due to the irregular breathing pattern, which demands advanced solutions. For this, rapid and precise sensors are needed in combination with embedded electronics for data acquisition, storage, and transmission.

Polysomnography is considered the gold standard method for the diagnosis of sleep disorders.[3] It is a comprehensive technique where multiple sensors are attached to the patient to monitor brain waves, blood oxygenation, heart rate, and eye and limb movements throughout the sleep study. This typically results in an extensive setup where the patient has to wear multiple sensors and is monitored overnight, typically in a healthcare clinical facility.[3] Hence, such multiparametric sleep monitoring has several disadvantages, including discomfort to the individuals, increased cost, and being unsuitable for home settings. Complementary technologies are being implemented such as wearable sensors[3,4] and sensors for breath pattern monitoring during sleep.[5,6] New non-obtrusive technologies are being developed to improve patient comfort and facilitate home use, including cameras for video-based photoplethysmography and near-infrared temperature measurements.[7,8] Despite being useful, these techniques are based on indirect observations and do not provide direct information for gas flow associated with breathing patterns.

Surface acoustic wave (SAW) devices have been used for respiratory monitoring applications, demonstrating fast response and good sensitivity,[9,10] including devices fabricated using a thin film piezoelectric approach.[11] Recently we developed a platform that combines SAWs with open-source electronics using Raspberry Pi hardware,[12] with the potential to be used for sleep disorder diagnostics and monitoring.[13] The platform includes thermal and standard imaging that could integrate video-based photoplethysmography and near-infrared monitoring. Moreover, the embedded system can be used for online or offline pattern recognition and analysis using time series[14,15] identification and machine learning methods.[16,17] For the thin-film SAW devices we use, changes in both relative humidity (RH) levels and temperature will cause shifts of frequency signals as a result of changes in acoustic velocity, which can be used to detect breathing. This is s combined effect of mass loading, surface sheet conductivity, and elasticity changes.[18]

In this paper, we investigate the ability of the SAW-Raspberry Pi platform to track and analyse breathing and the potential to detect breathing disorders. We aim to understand SAW-based breath tracking capability, as well as the combination of SAW temperature/humidity sensing with embedded electronics, as shown in Fig. 1. Currently, as a proof-of-concept setup, we simply use the SAW-Raspberry Pi platform to interface with a vector network analyser (VNA), record the frequency spectrum, and automatically track its changes. We have plans to substitute the VNA with reflectometer circuitry and radio frequency (RF) couplers to decrease the cost of the sensor. The platform offers the advantages of simplicity and potentially low cost without compromising performance.

II. DESIGN METHODOLOGY

A. Hardware description

Firstly, we explain the details of the electronic platform developed and its experimental data collection and analysis. The system is based on Raspberry Pi, Model 4, as an open-source embedded electronic processor. A similar system can also be implemented using another embedded platform, but our platform is more independent, relatively low cost, versatile, with good performance, and of an open-source nature. We provide the setup with a combined humidity and temperature sensor (Adafuit DHT22), with capacitive humidity reading and thermistor temperature-sensing functions. The humidity sensor chosen is a popular model that balances cost and performance; it is easily integrated with the Raspberry Pi and can work in wide temperature and humidity ranges. The sensor is connected to the GPIO pins of the Raspberry Pi, as shown in Fig. 2. Changes in resonant frequencies are monitored using a VNA (Keysight FieldFox Vector Network Analyzer) connected via USB. The embedded controller records such changes for time series representation, tracking peaks automatically. It should be noted that since SAW microfluidics are not required, the devices do not require RF power inputs and can be supplied power by the VNA, simplifying the setup.

B. Software description

Here we detail the development of the graphical user interface (GUI), implemented with Python due to the acceptance and scalability of the platform. The DHT22 sensor is connected to the Raspberry Pi and the VNA for referencing with ambient environments, frequency measurement, and drift compensation. We use the Python module Kivy[19] to develop a user-friendly environment at both the visualisation and ergonomic levels. Using this setup, we can present the actual frequency spectrum of the SAW device and its fundamental resonant frequency along with any drifts in real time. This will

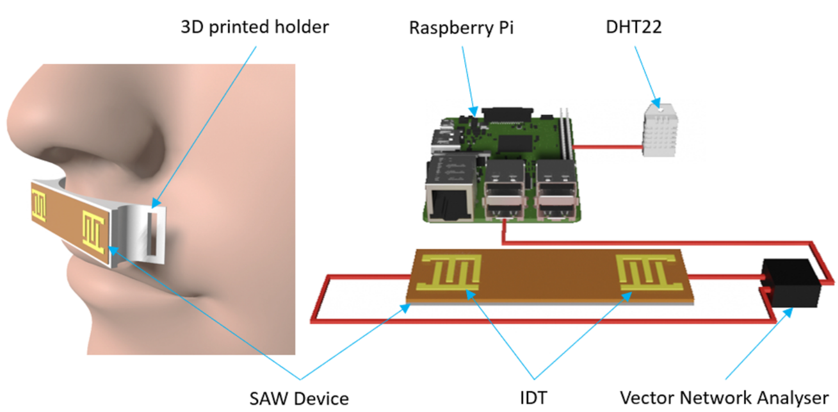


FIG. 1. Proposed apnoea-Pi platform.

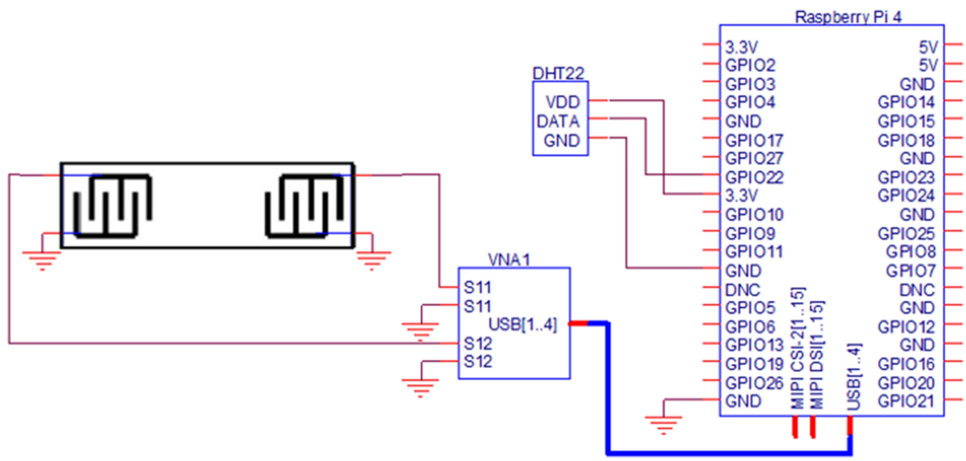


FIG. 2. Electronic schematic showing Raspberry Pi General Purpose Input Output (GPIO) connections to SAW devices.

be particularly useful to monitor, track, and balance frequency shifts due to temperature changes. The interface also represents readings of humidity and temperature in different plots. Data are recorded in the embedded system, using Python algorithms to perform pattern identification. For instance, with off-shelf Python libraries on machine learning, it is possible to match recorded real-time data with apnoea records, which can allow identifying the type of apnoea that the patient suffers and its severity (Fig. 3).

III. SAW DEVICE FABRICATION

The concept presented in this paper is suitable for SAW devices regardless of their fabrication and composition. We employ thin-film SAW devices with a bimorph Al/ZnO structure due to their potential to fabricate flexible SAWs.[20,21] Such SAW devices made with Al foil can be further made to be flexible and mounted on the upper lip of the patient, fitting comfortably and allowing adequate SAW sensing during sleep. The device can also be attached on the upper lip just below the nose in a breathing mask[22] with wireless connections to the embedded controller unit, as shown in Fig. 1. Further advantages of thin-film SAWs include industrial scalability and ultra-low-cost fabrication potential. In addition, thin-film SAWs have proved to be good humidity sensors for human breathing monitoring applications.[9,23]

Piezoelectric ZnO thin films were deposited on an Al plate (1.6 mm thickness). Magnetron sputter in direct current (DC) mode

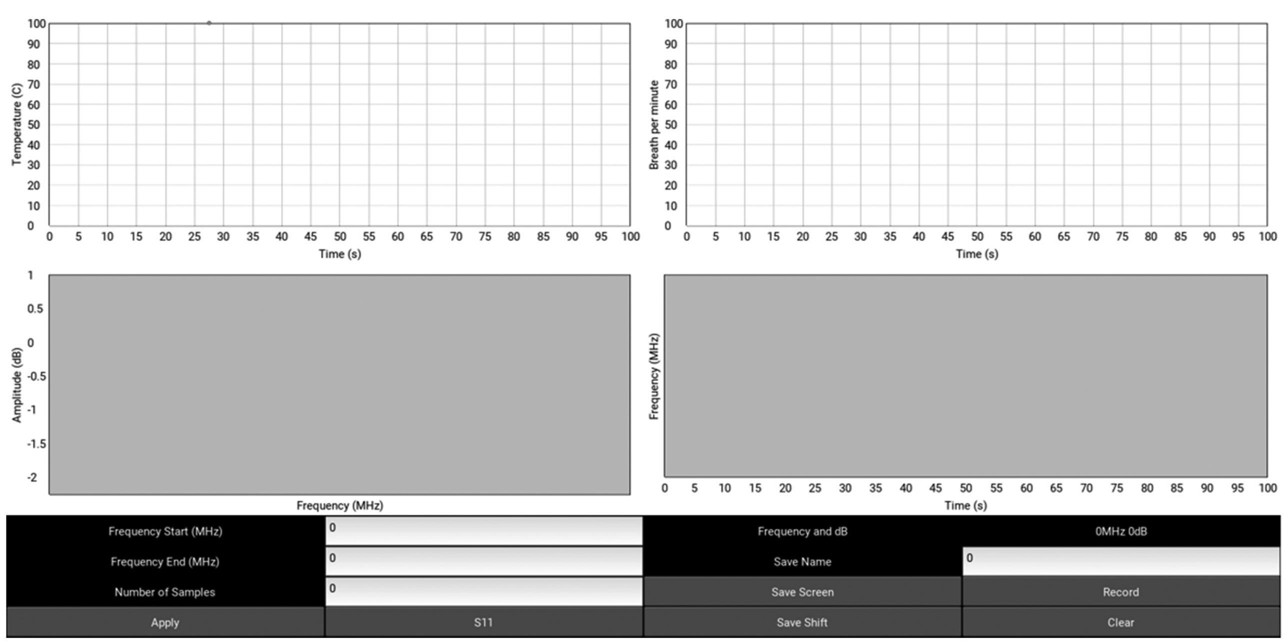


FIG. 3. GUI to monitor breathing patterns using SAW and humidity sensors.

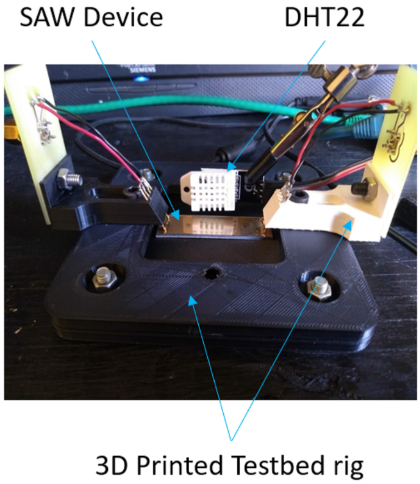


FIG. 4. 3D-printed testbed rig for testing humidity and temperature.

was employed for the thin film depositions using an Ar/O_2 flow ratio of 10/15 sccm and a Zn target (99.99% pure). The DC power was set to be 400 W, with a gas pressure of 4×10^{-4} mbar. A rotating sample holder was used during the deposition to realise the uniformity of the piezoelectric thin films. The deposition rate was 5.6 nm/min. Interdigital transducer electrode structures were made with standard lift-off photolithography. The electrodes were metallised by sputtering the Al target, achieving a thickness of 200 nm. The electrode design followed a standard finger pitching set at 200 μm, with an aperture of 5 mm and using 50 finger pairs. Resonance was measured at ~14.3 MHz (corresponding to the Rayleigh wave mode).

Reflection and transmission signals were measured using the VNA (Keysight Fieldfox vector network analyser, N9913A) to characterise the fabricated devices. Figure 4 illustrates the SAW platform, with the deposited ZnO film-on-aluminium-plate SAW device in a 3D-printed device test holder. We used a DHT22 combined humidity and temperature sensor, which was placed near the sensing zone of the SAW device. Electrode connections were made with spring-loaded pins.

IV. RESULTS AND DISCUSSION

A. Frequency responses to humidity and temperature

In this section we report the SAW frequency changes with humidity and temperature variations in the context of human exhaling patterns. Figure 5 is an example of the recorded signal of one prolonged exhale onto the SAW device and the commercial sensor DHT22. This example was typical of what happened when a patient was asked to take a deep breath, then exhaled towards both the SAW device and the DHT22 sensor. The thin-film SAW device showed a rapid change in frequency, taking 1.4 s to shift 50 kHz and 11 s to return back to the fundamental frequency of 14.276 MHz. The signals from the DHT22 took a much longer time to respond to the same breath level. The relative humidity (RH) peaked at 77%, an increase of 25%, and the signal from the DHT22 took ~7 s to respond to the exhale. The DHT22 also took a significantly longer time (35 s) to return back to the RH of the environment.

The following test consisted of 10 breaths. Figures 5(b) and 5(c) show the humidity breath signals recorded over several minutes. Humidity had large changes for each breath, with an increase of 10% to 20% RH, as shown in Fig. 5(a). Temperature, on the other hand, had a minimal change during breath cycles, as shown in Fig. 5(d), rather than gradually changing over the duration of the tests. The longer duration of breaths affected the temperature by as much as +2 °C.

There were two possible factors that could have affected the temperature readings near the SAW device. One was the continuous breathing of the patient under test, as the temperature inside a typical healthy human body is 37 °C. The temperature of an exhaled breath is around 34 °C.[24] The temperature of the SAW device was around 21 °C. The other factor was environmental temperature changes. This group of results was recorded at room temperature on a warm summer day (25 °C). Figure 5(d) clearly shows a steady rise in temperature over the duration of the test, which appeared to be unaffected by the breathing on the device. There were no noticeable spikes during exhaling, and no drops were observed when breathing was stopped. Therefore, this increase in temperature was likely caused by the environment changes due to the warming effect in the room.

In these initial tests, the device was held below the subject's nose perpendicular to the airflow direction. Ideally the device should be mounted parallel to the airflow directly below the nose. These tests showed slower deeper breaths. When exhaling longer or harder, a greater amount of air and water vapour were expelled from the participant. This moisture (i.e., tiny droplets) was deposited on the surface of the SAW device and took some time to clear, giving the signal a much longer recovery time to return to the fundamental frequency.

It is clear from these results that the SAW device responded quicker to humidity changes in comparison to the standard DHT22 sensor. It was possible for the DHT22 sensor to saturate when the patient breathed longer or stronger, while the SAW device showed a larger shift in frequency and thus had much higher sensitivity. The results showed that SAW devices are a much better choice in breath monitoring in the open-source electronic domain.

The commercial DHT22 sensor is useful for referencing and data-logging environmental changes surrounding the breathing test. However due to its very slow response, it is unsuitable for rapid changes caused by breathing. The sensor took an average of 7 s to return back to the original RH. While there may be a small temperature change on the surface of the SAW device, the commercial sensor was unable to detect any changes in the air surrounding the device. We only observed in one test that the recorded signal changed as a result of deep breathing closer to the sensor. In comparison, the SAW device could react 3 to 4 s quicker to the fluctuations in humidity, making this a much more suitable solution for monitoring breathing.

B. Simultaneously monitoring humidity and temperature

In order to observe the effect of humidity, hot airflow from a hair dryer was applied to the surface in order to reduce any moisture

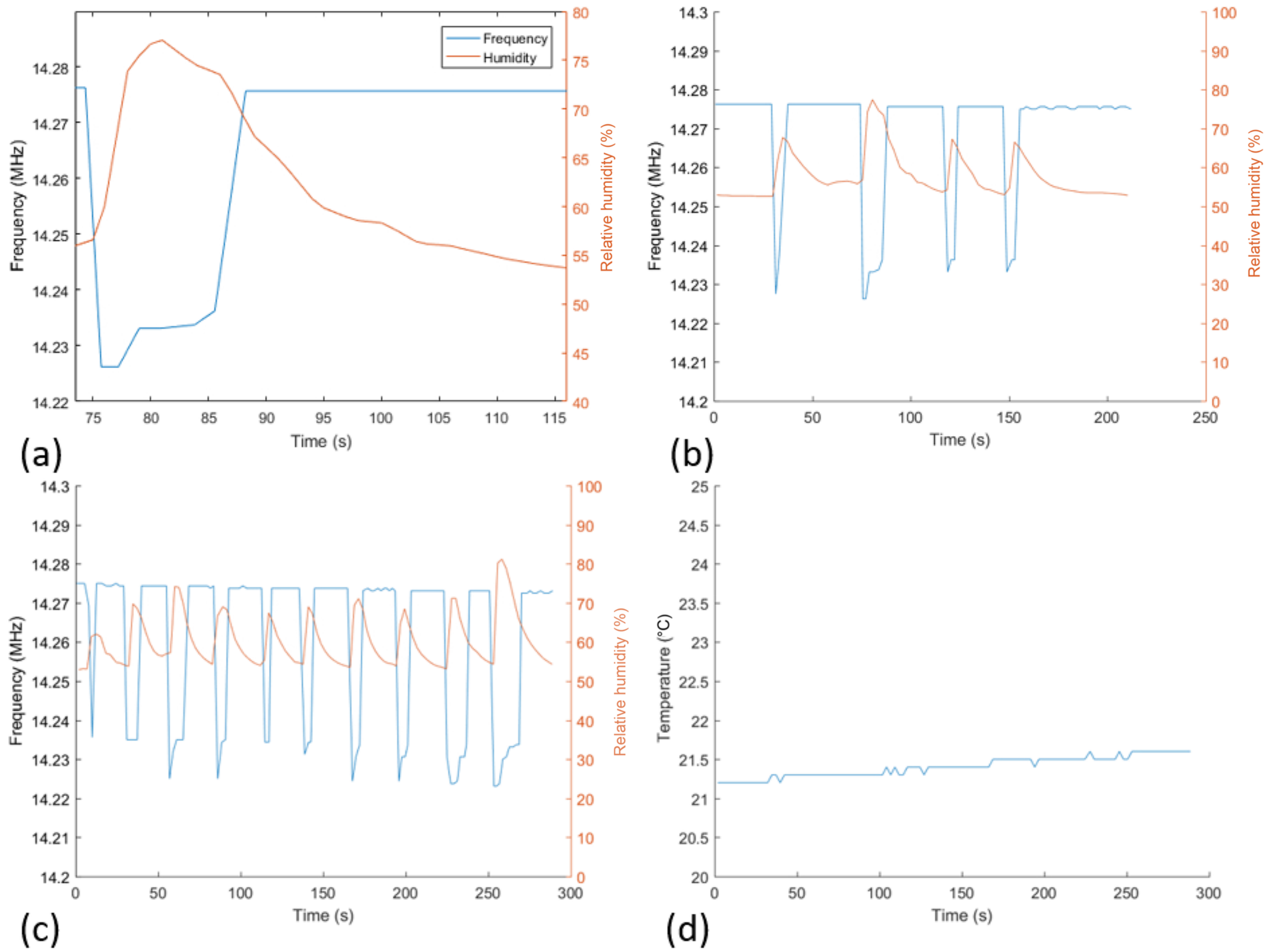


FIG. 5. The effect of humidity on frequency: (a) a single breath; (b) 5 exhales of approximately the same duration and strength; (c) 10 exhales; (d) temperature over test duration.

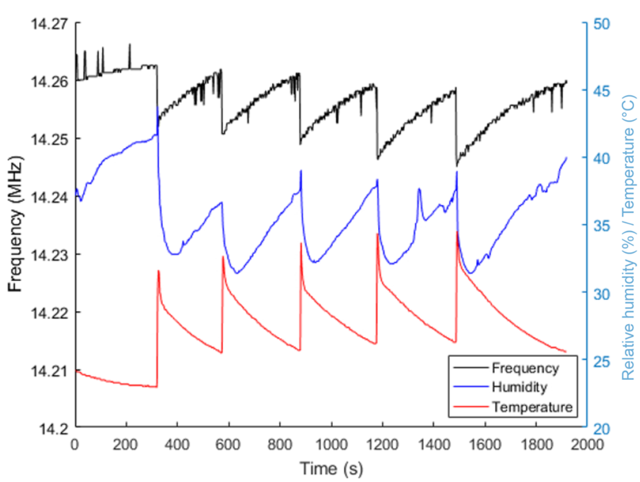


FIG. 6. Effects of hot air on the frequency shifts of the SAW device.

on the device. Figure 6 shows the frequency shift, temperature, and humidity readings from the DHT22 sensor. Using the previous method with temperature coefficient of frequency (TCF) calculations,[25] the large temperature fluctuations could be removed. It is worth highlighting that we could do all these calculation steps in real time with the embedded processor. As increasing temperature caused the device to expand, the speed of the waves decreased, and the fundamental frequency of the device decreased. Reducing humidity, on the other hand, increased the frequency by enhancing wave propagation, with less water-mass-loading effect on the device's surface. After filtering, the resultant signals clearly showed increases in frequency.

Figure 7 shows frequency and humidity extracted from the deep breathing and heating results. Above 50% RH, the data were recorded from deep breathing, and this half of the data showed a trend of rapid increases in frequency shift as the humidity approached 80%. This trend is similar to what has been reported in the literature.[26–28] As these data were acquired in the field during breath tests, there were other factors affecting the frequency shift, such as

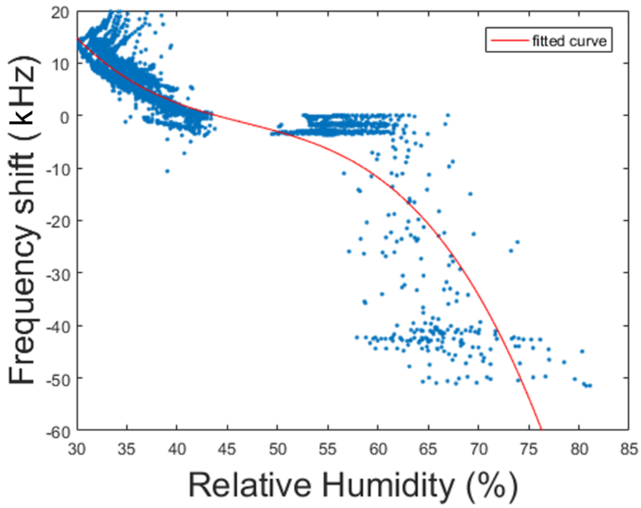


FIG. 7. Combined heating and breathing tests to calculate the effect of humidity on frequency.

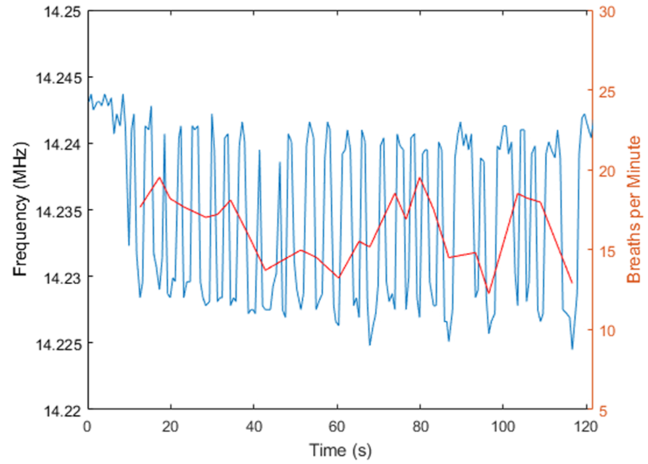


FIG. 9. Continuous normal breathing and calculated breaths per minute.

temperature. Temperature showed a much stronger influence in the hot air tests (all results below 45% RH), as humidity, which lowered the change in frequency, appeared to increase. Calculations to filter the effects of temperature were performed.

C. Temperature compensation

We obtained the actual frequency shift caused by humidity using the TCF of the device, which was measured to be −277.2 ppm. This enables the frequency changes from temperature to be calculated and deducted from the original signal data. This can also be applied in real time to the monitoring system.

Figure 8 shows the frequency, temperature, and estimated temperature-compensated frequency during the test, where the recorded temperature gradually increased by approximately 0.5 °C over 5 min. Using the calculated TCF for the device, it was possible to compensate for the effects of temperature on the frequency shift, reducing the chance of false peaks being detected.

D. Continuous breath detection and monitoring of apnoea cases

In breath tracking, real-time breathing identification is of utmost importance. Figure 9 shows the points that were detected in real time. The breaths per minute (bpm) rate is calculated based on the time recorded between peaks (averaged over 1 min). A simple breath detection method can be used to check the falling edge of each breath, running live as the breathing is happening. The time until the next breath is recorded, and the estimated bpm are calculated; this reading is then averaged, as there are variations between breaths within 1 min.

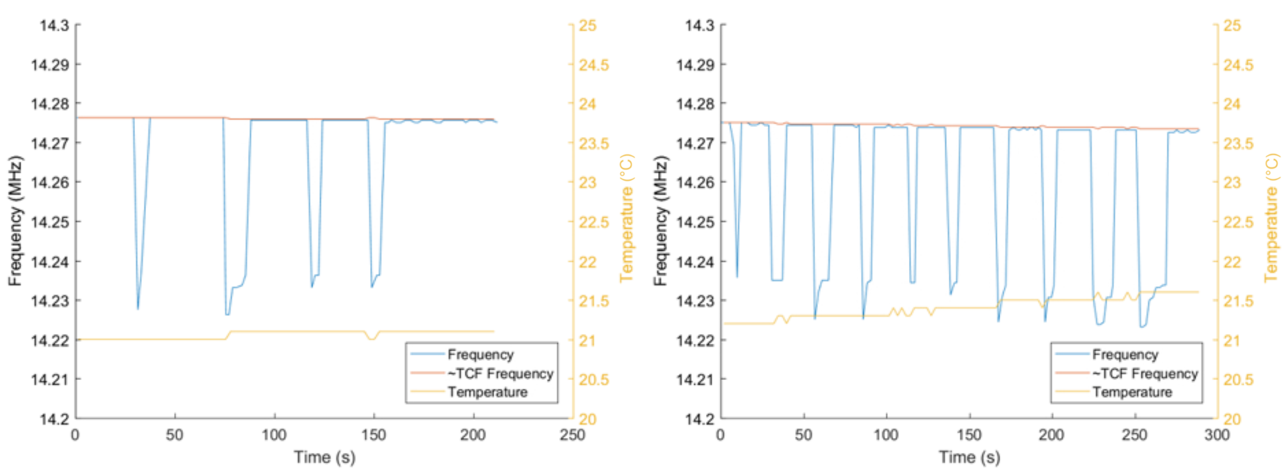


FIG. 8. Frequency, temperature, and temperature coefficient of frequency (TCF): (a) 5 breaths and (b) 10 breaths.

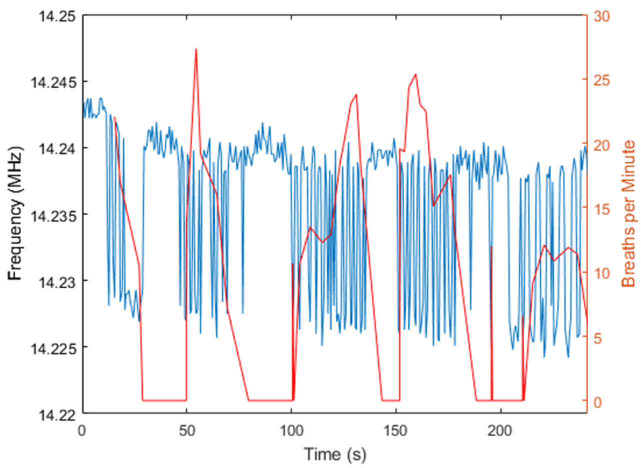


FIG. 10. Demonstration of a breathing disorder and calculated breaths per minute.

Figure 10 represents a breathing disorder such as apnoea. As shown in Fig. 10, the breathing is not normal, with a period of 30 to 50 s where no breathing has occurred. This is the raw frequency data captured from the SAW device. The sleep disorder is visually identified when the user has stopped breathing and when they resume. The detection algorithm also shows that the bpm momentarily drops below the average human breathing rate or completely to zero. This could be used to send alerts to a caregiver monitoring a person's health when their breathing is beyond their normal range. There is the potential for machine learning methods to be implemented and learn the normal behaviour of a patient, further increasing the accuracy and aid in detecting when the patient might require medical attention.

V. CONCLUSIONS

In this work we explain Apnoea-Pi, an open-source system for sleep disorder monitoring and identification using SAW sensors. The platform is adequate for all embedded computational platforms and SAW sensors. We show all the different aspects that the method needs to realise for sleep disorder tracking with proof-of-concept data. The technique is suitable for a wide range of SAW devices, including flexible substrates. The concept provides embedded computing capabilities for data storage, signal processing, and transmission. We show that the SAW humidity sensor interfaced by the embedded system is faster than standard capacitive electronic sensors. In future work we will implement machine learning protocols using open-source libraries. The idea is to complement SAW sensing with pattern identification and recognition capabilities, especially over long time series recording.

ACKNOWLEDGMENTS

This work was financially supported by the UK Engineering and Physical Sciences Research Council (EPSRC) under grant EP/P018998/1, as well as the UK Fluidic Network Special Interest Group of Acoustofluidics (EP/N032861/1).

AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

J.V. and P. C.-P. contributed equally to this work.

DATA AVAILABILITY

Data are available upon request.

REFERENCES

[1] Thorpy, M. International classification of sleep disorders. Sleep disorders medicine: Basic science, technical considerations and clinical aspects. 4th ed. Springer. 2017. pp. 475–484.

[2] Pavlova, MK, Latreille, V. Sleep disorders. Am J Med 2019;132(3):292–299. https://doi.org/10.1016/j.amjmed.2018.09.021.

[3] Zhang, H et al. Waist-wearable wireless respiration sensor based on triboelectric effect. Nano Energy 2019;59:75–83. https://doi.org/10.1016/j.nanoen.2019.01.063.

[4] Kwon, S, Kim, H, Yeo, WH. Recent advances in wearable sensors and portable electronics for sleep monitoring. iScience 2021;24(5):102461. https://doi.org/10.1016/j.isci.2021.102461.

[5] Ahmadzadeh, S, Luo, J, Wiffen, R. Review on biomedical sensors, technologies and algorithms for diagnosis of sleep disordered breathing: Comprehensive survey. IEEE Rev Biomed Eng 2022;15:4–22. https://doi.org/10.1109/rbme.2020.3033930.

[6] Feng, B, Zhao, K, Su, Q, Yu, Z, Jin, H. Passive wireless respiratory sensor. Electron Lett 2021;57(19):730–731. https://doi.org/10.1049/ell2.12248.

[7] van Gastel, M, Stuijk, S, Overeem, S, van Dijk, JP, van Gilst, MM, de Haan, G. Camera-based vital signs monitoring during sleep—A proof of concept study. IEEE J Biomed Health Inf 2021;25(5):1409–1418. https://doi.org/10.1109/jbhi.2020.3045859.

[8] Allen, J. Photoplethysmography and its application in clinical physiological measurement. Physiol Meas 2007;28(3):R1. https://doi.org/10.1088/0967-3334/28/3/r01.

[9] Tao, X et al. Three-dimensional tetrapodal ZnO microstructured network based flexible surface acoustic wave device for ultraviolet and respiration monitoring applications. ACS Appl Nano Mater 2020;3(2):1468–1478. https://doi.org/10.1021/acsanm.9b02300.

[10] Dinh, T, Nguyen, T, Phan, HP, Nguyen, NT, Dao, DV, Bell, J. Stretchable respiration sensors: Advanced designs and multifunctional platforms for wearable physiological monitoring. Biosens Bioelectron 2020;166:112460. https://doi.org/10.1016/j.bios.2020.112460.

[11] Fu, YQ et al. Advances in piezoelectric thin films for acoustic biosensors, acoustofluidics and lab-on-chip applications. Prog Mater Sci 2017;89:31–91. https://doi.org/10.1016/j.pmatsci.2017.04.006.

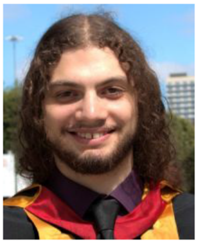
[12] Vernon, J et al. Acousto-Pi: An opto-acoustofluidic system using surface acoustic waves controlled with open source electronics for integrated in-field diagnostics. IEEE Trans Ultrason Ferroelectr Freq Control 2021;69:411. https://doi.org/10.1109/TUFFC.2021.3113173.

[13] Vernon, J, Canyelles-Pericas, P, Torun, H, Binns, R, Ng, WP, Fu, YQ. Apnoea-Pi: Sleep disorder monitoring with open-source electronics and acoustics. 2021 26th International Conference on Automation and Computing (ICAC). IEEE. 2021.

[14] Aguirre, LA, Barros, VC, Souza, ÁVP. Nonlinear multivariable modeling and analysis of sleep apnea time series. Comput Biol Med 1999;29(3):207–228. https://doi.org/10.1016/s0010-4825(99)00006-2.

[15] Cheng, C, Kan, C, Yang, H. Heterogeneous recurrence analysis of heartbeat dynamics for the identification of sleep apnea events. Comput Biol Med 2016;75:10–18. https://doi.org/10.1016/j.compbiomed.2016.05.006.

[16]Gutiérrez-Tobal, GC, Álvarez, D, Kheirandish-Gozal, L, del Campo, F, Gozal, D, Hornero, R. Reliability of machine learning to diagnose pediatric obstructive sleep apnea: Systematic review and meta-analysis. Pediatric Pulmonol 2021;57:1931. https://doi.org/10.1002/ppul.25423.
[17]Ramachandran, A, Karuppiah, A. A survey on recent advances in machine learning based sleep apnea detection systems. Healthcare 2021;9(7):914. https://doi.org/10.3390/healthcare9070914.
[18]Ciplys, D et al. Visible–blind photoresponse of GaN-based surface acoustic wave oscillator. Appl Phys Lett 2002;80(11):2020–2022. https://doi.org/10.1063/1.1459485.
[19]www.kivy.org. Kivy documentation. 2012. https://kivy.org/doc/stable/.
[20]Wang, Y et al. Flexible/bendable acoustofluidics based on thin-film surface acoustic waves on thin aluminum sheets. ACS Appl Mater Interfaces 2021;13(14):16978–16986. https://doi.org/10.1021/acsami.0c22576.
[21]Tao, R et al. Thin film flexible/bendable acoustic wave devices: Evolution, hybridization and decoupling of multiple acoustic wave modes. Surf Coat Technol 2019;357:587–594. https://doi.org/10.1016/j.surfcoat.2018.10.042.
[22]Tao, R et al. Hierarchical nanotexturing enables acoustofluidics on slippery yet sticky, flexible surfaces. Nano Lett 2020;20(5):3263–3270. https://doi.org/10.1021/acs.nanolett.0c00005.
[23]Li, D et al. A flexible virtual sensor array based on laser-induced graphene and MXene for detecting volatile organic compounds in human breath. Analyst 2021;146(18):5704–5713. https://doi.org/10.1039/d1an01059j.
[24]Cowan, JM, Burris, JM, Hughes, JR, Cunningham, MP. The relationship of normal body temperature, end-expired breath temperature, and BAC/BrAC ratio in 98 physically fit human test subjects. J Anal Toxicol 2010;34(5):238–242. https://doi.org/10.1093/jat/34.5.238.
[25]Tao, R et al. Bimorph material/structure designs for high sensitivity flexible surface acoustic wave temperature sensors. Sci Rep 2018;8(1):9052. https://doi.org/10.1038/s41598-018-27324-1.
[26]Xuan, W et al. High sensitivity flexible Lamb-wave humidity sensors with a graphene oxide sensing layer. Nanoscale 2015;7(16):7430–7436. https://doi.org/10.1039/c5nr00040h.
[27]Wu, J et al. Ultrathin glass-based flexible, transparent, and ultrasensitive surface acoustic wave humidity sensor with ZnO nanowires and graphene quantum dots. ACS Appl Mater Interfaces 2020;12(35):39817–39825. https://doi.org/10.1021/acsami.0c09962.
[28]Han, YC et al. Environment-friendly surface acoustic wave humidity sensor with sodium alginate sensing layer. Micro Nano Eng 2022;15:100127. https://doi.org/10.1016/j.mne.2022.100127.



Jethro Vernon received his MEng (Hons) in Electrical and Electronic Engineering from the University of Northumbria, UK in 2018. He is currently a Ph.D. graduate at the same university and is working with piezoelectric thin-film surface acoustic waves for biomedical applications. His experience and expertise are in the integration of electronics, sensors, and software.

Pep Canyelles Pericas received a dual BEng degree in Electrical and Electronic Engineering from the Technical University of Catalonia, Barcelona, Spain, and the University of Northumbria, Newcastle upon Tyne, UK in 2006, an M.Sc. degree in Engineering Management from the University of Sunderland, Sunderland, UK in 2008, and a Ph.D. degree in Control Systems from the University of Northumbria in 2016. Between 2009 and 2012, he worked as an optoelectronics research engineer at the University of the Balearic Islands, Palma, Spain. After receiving his Ph.D., he engaged with Innovate UK projects in the Knowledge Transfer Partnership and the Innovation to Commercialization of University Research schemes. Since 2019, he has been a researcher at the MESA+ Institute of Nanotechnology, University of Twente, Enschede, The Netherlands. His research interests are surface acoustic wave design, acoustofluidics, optical sensing, instrumentation, and control.

Hamdi Torun is an Associate Professor at Northumbria University. Previously, he was an Associate Professor at Bogazici University, Turkey. He is a cofounder of GlakoLens, a biomedical spinoff company. He received the Technology Award from Elginkan Foundation, Turkey in 2016, the Young Scientist Award from the Science Academy, Turkey in 2016, the Innovator Under 35 Award from MIT Tech Review in 2014, and the Marie Curie Fellowship (MC-IRG Grant) in 2011. His expertise is in development of integrated micro/nanosystems especially for sensing applications.

Richard Binns is the Head of the Department of Mathematics, Physics, and Electrical Engineering and an Associate Professor at Northumbria University, UK. Dr. Richard Binns graduated from Huddersfield University with a degree in Electronic and Information Engineering in 1993 and a Ph.D. in Analogue Test Strategies in 1997. He moved to Northumbria University in 2001 on an EPSRC post-doctoral contract looking into Analogue Synthesis tool development in collaboration with Ericson Components and Cadence Design Systems. His current research work includes the design of electronics for visible light communication, energy management in electric vehicles, radiation detection mechanisms for personal dosimetry, and power control systems development.

Wai Pang Ng (S'99-M'01-SM'08) received his BEng (Hons) in Communications and Electronic Engineering from the University of Northumbria, UK and his Ph.D. in Electronic Engineering from University of Wales, Swansea. He is currently the Deputy Head of Department and Associate Professor of Optical Communications in the Department of Maths, Physics and Electrical Engineering, Northumbria University, UK. He has worked as a Senior Networking Software Engineer at Intel Corporation. His research interests include radio-over-fibre, cognitive radio, high-speed optical communications, adaptive digital signal processing, and distributed fibre sensing.

Qiang Wu received BS and Ph.D. degrees from Beijing Normal University and Beijing University of Posts and Telecommunications, Beijing, China, in 1996 and 2004, respectively. From 2004 to 2006, he worked as a Senior Research Associate at City University of Hong Kong. From 2006 to 2008, he took up a Research Associate post at Heriot-Watt University, Edinburgh, UK. From 2008 to 2014, he worked as a Stokes Lecturer at Photonics Research Centre, Dublin Institute of Technology, Ireland. He is an Associate Professor/Reader with the Faculty of Engineering and Environment, Northumbria University, Newcastle Upon Tyne, UK. His research interests include optical fibre interferometers for novel fibre optical couplers and sensors, nanofiber, microsphere sensors for bio-chemical sensing, the design and fabrication of fibre Bragg grating devices and their applications for sensing, nonlinear fibre optics, surface plasmon resonance, and surface acoustic wave sensors. He has over 200 publications in the area of photonics and holds 3 invention patents. He is an Editorial Board Member of Scientific Reports, an Associate Editor for IEEE Sensors Journal, and an Academic Editor for Journal of Sensors.

Prof. Richard (YongQing) Fu obtained his Ph.D. degree from Nanyang Technological University, Singapore, and then worked as a Research Fellow at the Singapore-Massachusetts Institute of Technology Alliance, and as a Research Associate at the University of Cambridge. He was a lecturer at Heriot-Watt University, Edinburgh, UK, and then a Reader at the Thin Film Centre of the University of West of Scotland, Glasgow, UK before moving to Newcastle, UK in 2015. He has extensive experience in smart thin films/materials, biomedical microdevices, energy materials, lab-on-chips, micromechanics, MEMS, nanotechnology, sensors, and microfluidics. He published over 500 science citation index journal papers and 2 books, with a Google scholar H-index of 69.