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Review Paper

Review of Microphone-Based Contactless Vital Signs Monitoring Systems

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Microphones are sensors common to a variety of the Internet of Things (IoT) and healthcare applications. Many examples have proved that microphones can be useful in detecting, e.g., abnormal breathing rates. There are already applications that serve this purpose, e.g., respiratory acoustic monitoring, ResApp, etc. Breath signal was studied using a range of technologies and sensors, including the most common: radar, accelerometer, wearables, and so on. The majority of these sensors are attached to the body of a monitored person. However, the emergence of COVID-19 has drawn particular attention to the importance of using non-contact technologies for monitoring breath signals and other vital signs. This paper presents a comprehensive review of microphone-based non-contact vital sign monitoring, including the methodologies and concepts, while identifying new research gaps and opportunities for the future studies.

Keywords: beamforming; microphone; machine learning; vital signs.

Acronyms

CIR – channel impulse response,
DOA – direction of arrival
DYCTNN – dynamic convolution-transformer neural network,
FFT – fast Fourier transform,
FMCW – frequency-modulated continuous wave,
FPGA – field-programmable gate array,
IDRes – identity-based respiration monitoring system for digital twins enabled healthcare,
IoT – Internet of Things,
MEMS – microelectromechanical microphone,
NCVS – non-contact vital signs,
RIP – respiratory inductance plethysmography,
RMSE – root-mean-square error,
SNR – signal-to-noise ratio,
STFT – short time Fourier transform,
TDOA – time difference of arrival.

1. Introduction

The vulnerability of today's healthcare system was evident during COVID-19 pandemic, a serious global concern in which the number of patients outweighed available equipment. It was a common practice that the respiratory apparatus, known as ventilators, was shared between two patients (Garzotto *et al.*, 2020). According to (Branson, Rodriquez, 2023; Tsai *et al.*, 2022), the use of ventilators increased by 30 % in case of adults and 15 % in case of children following COVID-19. This indicated that persons with normal breathing problems have been neglected during this period. This group of people includes both the younger and older generations.

The application of digital processing to a microphone signal makes it suitable for various research applications. Microphones, commonly used for recording audio, have now evolved into sophisticated non-contact monitoring sensors. By using advanced signal processing techniques, microphones can be used to sense and analyze vital signs such as heart rate and respiration rate without making contact with the body of the target. This new approach offers numerous advantages over traditional methods, resulting in microphone-based non-contact monitoring systems being a promising technology for remote health monitoring and wellness applications.

A microphone is a transducer that converts sound waves to electrical signals. It detects slight changes in air pressure induced by sound and generates an electrical signal representing the acoustic sound waveform. This electrical signal can subsequently be amplified, processed, recorded, or transmitted for numerous purposes such as telecommunications, audio recording, active noise control and speech recognition. Microphones vary in kind, design, and technology, but they always work on the principle of converting acoustic energy (sound pressure) into electrical energy. Common types of microphone include dynamic, condenser, ribbon, piezoelectric microphones and microelectromechanical microphone (MEMS); each comes with different properties that make it best suited for different applications.

Numerous studies have been conducted in the area of contact and non-contact vital signal monitoring. Among the research results, a few include thermal imaging cameras (Savazzi *et al.*, 2020), photoplethysmography (PPG) (Ryu *et al.*, 2021; Artemyev *et al.*, 2020; Boccignone *et al.*, 2023; Hashim *et al.*, 2023; Khong, Mariappan, 2019), doppler radar (Islam *et al.*, 2019; Joshi *et al.*, 2023; Edanami *et al.*, 2022; Zhang *et al.*, 2023a; Wahyu *et al.*, 2022; Mercuri *et al.*, 2018), microwave sensors (Katoh *et al.*, 2023; Celik *et al.*, 2011; Dei *et al.*, 2009), and acoustic sensors (Okamoto *et al.*, 2023; Xiao, Yu, 2021; Liu *et al.*, 2022; Jahanshahi *et al.*, 2018; Smithard *et al.*, 2017). Other popular choices are video cameras (Huang *et al.*, 2021; Sabokrou *et al.*, 2021; Artemyev *et al.*, 2020; Hsu *et al.*, 2020; Shokouhmand *et al.*, 2022) and fiber cable (Xu *et al.*, 2020; 2021; Liang *et al.*, 2023; Zhao *et al.*, 2023; Lyu *et al.*, 2022). However, using microphones for non-contact recording offers several advantages, including robustness, the ability to capture detailed information (Kranjec *et al.*, 2014; Fang *et al.*, 2016) and their sensitivity across a wide range of coverage, making them adaptable to different scenarios. Microphones are also useful for making respiratory sounds accessible via phones, laptops, and other portable devices (Massaroni *et al.*, 2021), although this approach has its own drawbacks. This review focuses on microphones for non-contact vital sign monitoring and it is divided into sections discussing various methods that have been developed in this field. These methods include beamforming techniques, smartphone-based solutions, hardware and artificial intelligence (AI) based approaches.

2. Microphone

The advent of the Internet of Things (IoT) has made the use of microphones more relevant, increasing their usefulness by 17% per year (Beckmann, 2017). This may be a result of microphones changing from just a device for voice reception to their adaptation to mobile applications. Modern applications of microphones include mobile phones and tablets, cameras, wearables, bluetooth speakers, and security cameras. They can act as a sensor for detecting the respiration or heart rate of humans. Different microphones are being used in sound analysis due to their unique capabilities and features (Balgemann *et al.*, 2023). Moreover, some of them are equipped with a digital signal processor that enables them to modify the audio signal based on the distance and direction to the sound source. The pulse-density modulated microphone has been recently gaining attention due to its ability to delivering audio to digital processors, but its high-order decimation filter for pulse code modulation increases the cost and power consumption when used as a beamformer (Ipenza, Masiero, 2018). Table 1 shows a summary of microphone applications found in the literature.

2.1. Types of microphones used in audio signal analysis

2.1.1. Dynamic microphones

Dynamic microphones have the advantage of providing balanced sound recording. They are also durable,

Table 1. Applications of microphones from the literature.

Paper	Microphone type	Placement	Contact/Non-contact
(Doyle, 2019)	Electret	Attached to trachea, lungs	Contact
(Valipour, Abbasi-Kesbi, 2017)	Capacitor	Chest region	Contact
(Kavsaoğlu, Sehirli, 2023)	Stethoscope	Chest region	Contact
(Zhang *et al.*, 2023b)	MEMS	–	Non-contact
(Shih *et al.*, 2019)	Smartphone	Mouth/Chest	Contact
(LoMauro *et al.*, 2022)	–	Chest wall and lungs	–
(Dafna *et al.*, 2015)	Rode NTG-1 directional	–	Non-contact
(Islam *et al.*, 2021)	Wearable and smartphone	Chest region	Contact
(Chauhan *et al.*, 2017)	Smartphone and wearable		Contact
(Khodaie *et al.*, 2021)	MEMS	Mouth region	Contact
(Khatkhate *et al.*, 2022)	Pressure sensors	Ribcage	Contact
(Fang *et al.*, 2023)	Circular microphone array	–	Non-contact
(Xu *et al.*, 2022)	Smartphone	–	Non-contact
(Xie *et al.*, 2020)	–	Modelling of chest region	Contact

portable, and capable of producing high-quality sound. These microphones work on the principle of electromagnetic induction, the movement of a wire in a magnetic field creates an electromotive force (EMF) in the wire, which forces the current to flow. When sound waves hit the diaphragm, it moves either the magnet or the coil, creating a small current that can capture sounds from up to one meter away.

2.1.2. Condenser microphone

This kind of microphone functions as a capacitor consisting of two plates near each other, one of which acts as the diaphragm. When sound reaches the diaphragm, it vibrates, generating changes in capacitance, resulting in an electrical representation of the acoustic signal. Condenser microphones have a standard diaphragm diameter: large and small; the small having the advantage of being more compact and sensitive to picking up higher frequency sound (PreSonus, 2022). Its high fidelity, excellent frequency response, low noise levels, and sensitivity make it appropriate for acoustic research (Todorović *et al.*, 2015).

2.1.3. Electret microphone

An electret microphone is a type of condenser microphone that eliminates the need for a high-voltage power supply by using a permanently charged material called an electret. Like most microphones, it consists of a diaphragm placed near a metal backplate, forming a capacitor. When sound waves impinge on the diaphragm, it vibrates and changes the capacitance, generating an electrical signal corresponding to the sound. They are commonly used in devices such as mobile phones, hearing aids, and voice recorders because they are compact, less expensive, and they require a small power source for their in-built preamplifier (Open Music Lab, 2022).

2.1.4. Microelectromechanical microphone

The MEMS microphone operates by using a tiny mechanical system etched onto a silicon chip to convert sound waves into electrical signals. It is made of a flexible diaphragm and a fixed backplate which forms a variable capacitor. The capacitance of the capacitor changes as sound waves hit the diaphragm, and this change/variation is then converted into an electrical signal by an integrated circuit. MEMS microphones are gradually replacing electret microphones due to their smaller size and greater suitability for smartphones. They have the advantage of picking up signals equally from all directions, making these microphone omnidirectional. They are also tiny in size and consume low amount of power. This implies they can be used to determine the direction of sound in a microphone array (Wang *et al.*, 2020). However, when MEMS microphone recordings are converted to electrical signals, some noise is introduced (Rose, 2022). The audio data used in smartphones is generated digitally as a result of current movement in a very small mechanical sound diaphragm. MEMS microphones are employed in mobile devices because of its tiny footprint and good performance (Picchio *et al.*, 2019).

Table 2. Comparison of non-contact health monitoring technologies.

Technology	Strengths	Weaknesses	Applications	References
Microphone-based	Low cost, high accuracy in detecting physiological sounds, easy integration with existing devices, non-invasive, versatile, low power consumption	Sensitive to noise, privacy concerns, limited range 0.5 m–1 m for breath sounds	Respiratory monitoring, heartbeat detection, speech recognition	Fukuda *et al.*, 2018; Aarts, 2019; Genova, 1997; Sharma *et al.*, 2019
Radar-based	Accurate for motion detection, capable of detecting chest movements for breathing rate monitoring, non-contact, works in the dark	Expensive hardware, limited in detecting internal physiological sounds, consumes more power than other methods, long range between 10 m and 50 m	Breathing rate monitoring, heart rate monitoring, motion detection	Sakamoto, Yamashita, 2019; Zakrzewski, 2015; Lv *et al.*, 2021
Infrared sensors	Effective for detecting body temperature changes, non-contact, can detect presence or absence based on heat signatures, variable power consumption	Requires line-of-sight, affected by ambient temperature variations, limited to surface-level observations, calibration needed, range between 0.1 m to 4 m	Body temperature monitoring, motion detection, sleep studies	Thundat *et al.*, 2000; Fraden, 2014; Yang *et al.*, 2022
Ultrasonic	Good for distance measurement and obstacle detection, non-contact, safe to use, non-invasive, low power consumption	Limited resolution for detecting fine physiological details, requires direct path for sound waves, affected by material properties, range between 0.3 m to over 10 m	Fall detection, obstruction detection, motion monitoring	Hoctor *et al.*, 2008; Barany, 1993; Toa, Whitehead, 2019

2.2. Comparison of non-contact health monitoring technologies

A microphone-based non-contact monitoring system is a better alternative to other non-contact monitoring methods such as radar, infrared and ultrasonic sensor. It is capable of monitoring breath signal, heartbeat detection and identifying vocal patterns. These capabilities are possible due to its ability to leverage on the properties of sound waves to monitor physiological features. Table 2 outlines the advantages and disadvantages of these methods.

2.3. Microphone array

A microphone array (MA) is an arrangement of several microphones positioned to gather signal from different spatial locations. The main goal of MA is a robust representation of the signal. It works on the principle of sound propagation that several inputs are able to either attenuate or enhance by processing signals from specific directions even in the presence of noise (Dey, Ashour, 2018; Levy *et al.*, 2010; Doclo *et al.*, 2015). MAs are essential in non-contact measurement of signals, leveraging on the combined power and sensitivity of the connected microphones. The spatial arrangement of MA consists of several configurations which include linear arrays, circular arrays or spherical arrays, depending on the purpose an array is intended (Alexandridis, Mouchtaris, 2017). The configurations also determine the spacing between the connected microphones (Dey, Ashour, 2018). Exemplary array arrangements are shown in Fig. 1. In this configuration, the microphone may be replaced with a smartphone or a beamforming method. The difference between a single microphone and an array arrangement is that a single microphone cannot provide the direction of a sound source and reduction of reverberation without the need for post-processing. An array arrangement, on the other hand, can improve the speech signal quality using the received radiation pattern from the direction of a desired signal, thus improving the signal-to-noise ratio (SNR) (Dey, Ashour, 2018).

Two important terms associated with array arrangement is beamforming and the direction of arrival (DOA). Beamforming is the procedure of estimating DOA and can be defined as a process of changing the phase and amplitude of signals received by an array of sensors (in this case microphones). The goal of beamforming is to enhance the signals from one direction while suppressing the other directions, to make the received signal specific to a direction. There are two major types of beamforming: data-dependent and data-independent. Data dependent methods usually change parameters based on the received signal example are adaptive or optimal, phase-shift frequency beamforming. Data-independent (or fixed) beamforming have fixed parameters; examples include delay-and-sum, filter-and-sum, subband, and minimum variance distortionless response beamforming (Mathworks, n.d.). The DOA, on the other hand, is a process of determining the direction (for example, in degrees) in which a received signal was transmitted. The degree of accuracy of the estimated DOA is affected by the performance of beamforming, thereby making beamforming and DOA interdependent on each other.

3. Principles of microphone-based monitoring

Microphone-based health monitoring systems utilize the body's natural sounds (signals), such as breathing, heartbeats, and coughing, to obtain vital physiological data. By detecting these acoustic signals, these systems can constantly and non-invasively monitor an individual's health, as a suitable alternative to contact-based devices. Microphones are sensitive to the vibrations caused by physiological events like airflow during respiration, heart valve closures, or even vocal cord vibrations. The vital signals monitored by the microphones include heart rate, respiratory rate, snoring and coughing.

3.1. Signal processing techniques

The accuracy and effectiveness of a microphone in monitoring vital signs depend largely on the parameters of the microphone itself and possibly on the preamplifier working with it. These factors should be well supported by the signal processing method adopted. Recorded information contains noise and other unnecessary data, necessitating the use of filtering techniques to extract important signals.

a) b) c) d)

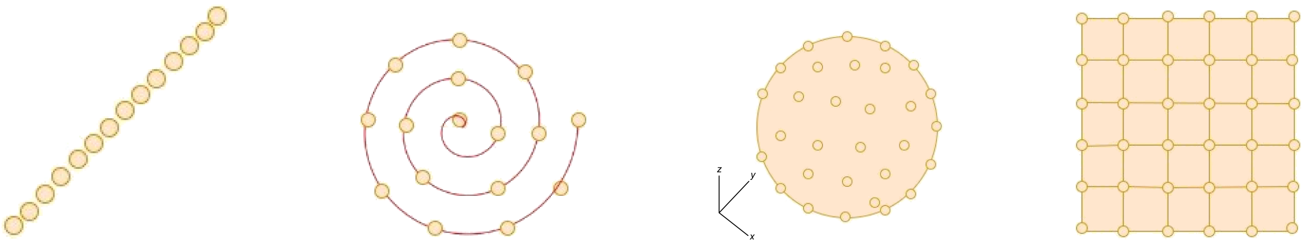

Fig. 1. Different array arrangements: a) linear array; b) spiral array; c) circular array; d) planar array.

3.1.1. Noise filtering and amplification

A significant challenges in microphone-based monitoring is the capture of background noise (Llorca-Bofi *et al.*, 2024; Paul *et al.*, 2023). This noise can degrade the quality of the acquired signal, making it difficult to the isolate desired signal. Noise can be addressed using numerous filtering techniques. For example, band-pass filter can clearly separate breath signals from noise, as the frequency of the breath signal is between 100 Hz and 1000 Hz while heart sound ranges between 20 Hz to 200 Hz (Han *et al.*, 2023). Other filtering methods such as low pass and high pass filters can also be applied to recover a desired signal. Amplification is essential for enhancing low-amplitude signals, such as shallow breath signal.

3.1.2. Adaptive filtering

Adaptive filtering is a signal processing technique commonly used in noise cancellation, system identification, channel equalization and control systems. The major difference between an adaptive filter and other types of filters is its ability to dynamically adjust its coefficients in response to changes in the signal environment (Arenas-Garcia *et al.*, 2021). This dynamic adjustment makes it suitable for processing a non-stationary signal, such as the breath signal. One common example of a adaptive filter is the adaptive line enhancement (ALE). ALE uses adaptive filters with dual roles: predicting the narrowband component of a noisy signal and enhancing them while eliminating broadband noise. ALE assumes that the narrowband signal is either sinusoidal or periodic, allowing it to exploit the time correlation in the narrowband signal to distinguish between the original or desired signal from the uncorrelation broadband noise. To improve the quality of the desired signal, ALE uses the previous input to separate the narrowband components from the broadband noise. The basic components of ALE include the input signal, the delay lines, the adaptive filter, and the computed error signal. The use of ALE in microphone-based, non-contact health monitoring is important, as one of the challenges associated with microphones is their tendency to pick up background noise along with the desired signal. ALE can be applied to solve this problem (Atkins *et al.*, 2021).

3.1.3. Time-domain and frequency-domain analysis

Signal features can be extracted using either time-domain or frequency-domain analysis. The time domain describes changes in a signal amplitude with respect to time and is useful for detecting breath cycles or heartbeats. On the other hand, frequency domain analysis, examines the signal energy's distribution across a range of frequencies, which helps identifying specific physiological signals characterized by specific frequencies (Rangayyan, 2015). A common example used in frequency domain analysis is the fast Fourier transform (FFT), which coverts a time domain to the frequency domain for more detailed analysis of its frequency components (Henry, 2023). Furthermore, the time-frequency distribution (TFD) combines both time and frequency domain information, providing a more comprehensive analysis when both time and frequency domain information are needed simultaneously.

3.1.4. Machine learning and AI integration

Recent advancements in microphone-based non-contact health monitoring system focus on integrating machine learning (ML) and AI. These algorithms enable the model to identify, classify and interpret physiological signals. For example, deep learning models such as convolutional neural network (CNN) and long short term memory (LSTM) networks are used to distinguish normal and abnormal breath or heartbeat patterns (Li, Qian, 2024; Roseline *et al.*, 2024). Additionally, these algorithms can handle large datasets and learn from previously collected physiological signals, improving accuracy. Numerous ML- and AI-based methods have been used for the identification and classification of different types of coughs, wheezes or heart signals (Ferrante *et al.*, 2020; Orlandic *et al.*, 2021; Pramono *et al.*, 2019; Renjini *et al.*, 2021). In a case when microphone records patient's respiratory signal, the raw data serves as an input to the AI-powered system, which filters out (remove) noises, identifies key features, and classifies the data based on the trained model. This facilitates real time diagnosis of diseases associated with breath and heartbeat signals.

3.1.5. Pattern recognition and feature extraction

Pattern recognition plays a crucial role in identifying acoustic signal. The algorithm detect repetitive patterns in the signal, such as peaks in the amplitude or the periodicity of heartbeats and breathing cycles. The wavelet transform is a commonly used feature extraction method, and it decomposes complex signals into simpler components, allowing unique characteristics that may indicate the presence or absence of diseases to be clearly identified (Taghavirashidizadeh *et al.*, 2022).

4. Beamforming based methods

Beamforming can be defined as the process of combining multiple signals from microphones in an array to amplify sound in a specific direction. Beamforming can be combined with other approaches, such as radar systems and cameras, to locate targets (Xiong *et al.*, 2023; Wang *et al.*, 2023). To detect a signal in a specific direction, the beamformer controls the phase and amplitude at the transmission end. In non-contact vital sign monitoring, beamformers ensure accuracy measurement of vital sounds and allow monitoring of multiple subjects at the same time. Frequent body movementa and noise are among the main factors hindering beamforming. This section reviews literature that has adopted beamforming.

A dynamic convolution-transformer neural network (DYCTNN) for sound source localization using functional beamforming was proposed by Zhang *et al.* (2024). Dynamic convolution and self-attention techniques were used to capture the spatial distribution of sound sources. The model was trained and tested using a dataset generated via acoustic simulation on a 2 m × 2 m plane with a 60-channel spiral microphone array and one to five monopole sources producing sound fields at various frequencies. Xiong *et al.* (2023) utilized beamforming by combining a phased array of an antenna and a double-phase shifter (DPS) to adjust the magnitude and phase of the transmitted signal. Beamforming allowed for simultaneous monitoring of numerous people with minimal target interference. Actuators were utilised to simulate human chest movement, while an omni-antenna was employed to generate and receive signals. This method worked well; however, adding antennas make this system too complex.

Sun *et al.* (2022) used a phase-shifting technique for transmitting beam formation and digital beamforming for optimal spatial filtering at the receiving end. The method utilized a frequency-modulated continuous wave (FMCW) radar with 9 transmitting and 16 receiving channels. Digital beamforming was designed to obtain optimal spatial filtering at the receiving end, enhancing the capability of multi-person detection. The arctangent demodulation method was used for phase estimation, and phase unwrapping was thereafter applied to address phase ambiguity. The proposed method was able to detect targets within the range of 1.8 m to 12 m. Hall *et al.* (2015) developed the phased array non-contact vital sign (NCVS) sensor system with an autonomous beam steering algorithm, implemented in LabVIEW. The selected phased array arrangements were tested, and data samples were gathered to assess the performance of the autonomous beam steering algorithm. The results showed that heart rate measurement accuracy was approximately 95 % within 5 bpm, and the automatic beam steering algorithm achieved an accuracy of 94.36 % within 5 bpm with a 2.82 bpm standard deviation.

Wang *et al.* (2023) introduced the dualforming-based method that combined both spatial and frequency domain beamforming to improve the signal-to-noise ratio (SNR) across multiple subject locations. The multiple subtle signal classification (MUS2IC) approach was used to separate subjects with subtle movements from static objects. Empirical mode decomposition (EMD) was used to extract heartbeat patterns by decomposing the cardiac frequency response (CFR) streams into separate intrinsic mode functions (IMFs). The method measured heart rate within a 10 m range, allowing the monitoring of heartbeats of six subjects at the same time. Tashev and Acero (2006) presented a post-processing a microphone array's beamformer output. The algorithm estimated the spatial probability of sound source presence and applied a spatio-temporal filter. Experimental results showed that the directivity index improved up to 8 dB and jammer suppression up to 17 dB at the angle of 40° from the sound source.

5. Microphone sensor based method

A microphone can detect vital signals in both contact and non-contact modes. The latter produces less noise since the sensors are not in direct contact with the subject's body. This section explores various studies conducted in this area. A simple diagram of the microphone-based method is shown in Fig. 2.

Chen *et al.* (2015) presented a microphone position calibration approach to distribution microphone arrays, combining an acoustic energy decay model with the time difference of arrival (TDOA) method. The method first estimates the coarse distance between the microphone and the sound source, followed by TDOA to find the accurate distance within a specific range near the coarse distance. The microphone's position is determined using the least mean square error estimate approach, which yields high positioning accuracy, steady calibration performance, and low processing complexity. Qian *et al.* (2018) employed FMCW sonar to send a chirp signal and calculated the spectrogram of the baseband signal to extract vital signals such as breath rate, heart rate, and individual

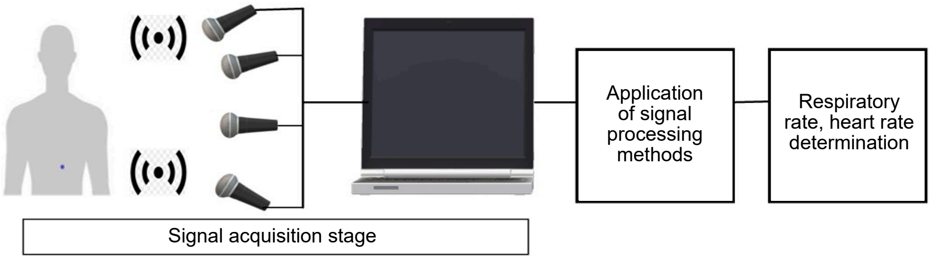

Fig. 2. Typical diagrammatic representation of vital signs monitoring system setup using microphone.

heartbeat from the acoustic signal phase. The method downsampled the FMCW signal to baseband and continually monitored the signal phase in the spatial bin containing vital motions. The use of dual microphone enhanced the performance of the system.

Valipour and Abbasi-Kesbi (2017) monitored heartbeat and respiration rate using a phonocardiogram based miniature wireless acoustic sensor with two capacitor microphones, a microprocessor, and a transceiver operating at 2.54 GHz in the industrial, scientific, and medical (ISM) band. The sensor was placed on the volunteer's chest, and ECG signals were acquired. The findings showed root-mean-square errors (RMSEs) of less than 2.27 bpm for heartbeat and 0.92 bpm for respiration rate, with standard deviation of less than 1.26 for heartbeat and 0.63 for respiration rate. Overall, the developed approach is contact-based. Tran *et al.* (2014) used a hybrid hardware-software technique to detect an infant's vital signs, using an infrared non-contact temperature sensor and a microphone-based breathing sensor. The system was designed in a hardware description language (HDL) and implemented on an field-programmable gate array (FPGA) board. The developed device identified the infant's vital signs when tested on the Altera DE2-115 FPGA board.

Taniguchi *et al.* (2023) presented a vital sign monitoring system for dogs based on the MEMS microphone and the Raspberry Pi wireless system. To extract the heart rate, they first removed the DC offset from the obtained data, then transformed it using the short time Fourier transform (STFT), and finally applied the fifth-order Butterworth bandpass filter. The filtered data was then normalised, and the heart rate was calculated by counting amplitude peaks within a specific time frame. The heart rate extraction technique includes calculating the number of data points and amplitude thresholds, as well as computing the distance between peaks. The heart rates acquired during the surgery were monitorable every second, with an average heart rate of 110 bpm.

Dafna *et al.* (2015) proposed a non-contact microphone-based polysomnography (PSG) to measure breathing noises and estimate breath rate during sleeping. Adaptive noise reduction techniques was used to suppress background noise and non-periodic spectrum components were filtered out by a periodicity augmentation module. The BR module was the final stage, and it estimated BR based on the filtered signal. The system was tested on 204 individuals who participated in an in-laboratory in the study. The Pearson correlation coefficient between the two techniques was $R = 0.97$, showing a strong relationship. An epoch-by-epoch BR comparison revealed a mean relative error of 2.44 % and Pearson correlation of 0.68, demonstrating good agreement between the audio-based BR estimation and the gold-standard respiratory belts.

Wang *et al.* (2021) presented a low-cost, contactless heartbeat monitoring device based on a commodity speaker and a microphone array. Acoustic impulses are transmitted by a speaker and received by a microphone array to estimate the human heartbeat. Passive beamforming and frequency domain filtering were used to improve the quality of the signal accuracy. A wideband time-delay approach was also used to predict the DOA of the target-reflected signal. The prototype monitors heart rate at a distance of 1.7 m, with an estimation error of 0.5 bpm. A wearable microphone sensor based on the adaptive windowing technique was employed by Zhang *et al.* (2024) to estimate heart rate. The method used a spectrogram to derive an initial estimate and calculate the optimal window length based on frequency resolution and physiological constraints. A one-step autoregressive model was used to correct estimates, thereby improving the heart rate measurement accuracy by ±2.8 bpm. The developed method was tested on a group of 26 healthy subjects. Ashraf and Moussavi (2024) designed a piezoelectric surface microphone placed at the suprasternal notch to capture tracheal breathing sounds. This device produced clear respiratory waveforms with minimal sensitivity to ambient noise. A wearable accelerometer microphone (Gupta *et al.*, 2021) captured lung sounds and chest-wall motion to derive respiratory patterns in hospitalized patients with COPD, pneumonia, etc. These contact sensors can measure both breath sounds and rate with high fidelity, even amid patient motion or background noise; for example, the piezo sensor showed negligible degradation across frequency bands when noise was present.

6. Smartphone and contact based methods

Smartphone technology started in 1992 (Tocci, 2024), and it has surpassed expectations, particularly in the development of applications that can run on smartphones. A significant contributor to this success is the microphone, which has helped acquisition of data for various applications, including those focused on vital sign monitoring. Smartphones are now capable of monitoring vital signs such as heart rate, respiratory rate, blood pressure, and blood oxygen saturation, whether through contact-based or non-contact methods. The section focuses on the literature that has used microphones installed in smartphone for vital sign monitoring.

Kavsaoğlu and Sehirli (2023) captured audio signals from the heart and trachea, resulting in a dataset for detecting inhalation and exhalation circumstances. Two methods were used to obtain these signals: one involving heart sound and the other involving trachea sounds. The audio signals were classified into inhalation and exhalation phases using ML models. The highest accuracy and performance were achieved using a majority voting strategy with k-nearest neighbour, random forest, and support vector machines. Doyle (2019) used a flat adhesive acoustic sensor and the TASCAM DR-40 Digital Recorder to record bioacoustic data. Recordings were taken from multiple of locations, including the neck, external ear canal, oxygen mask, as well as a leak-free microphone attached to a laryngeal mask airway. Audacity, an open-source digital audio editor and recording programme, was used to analyse breath sounds and apply digital filters.

Lee *et al.* (2023) used an array of MEMS microphones to record lung sound waves, which were converted into acoustic images. The system's performance was assessed using waterbags to stimulate airway blockages, and its accuracy was compared to that of digital stethoscopes. The proposed method demonstrated better detection of lung conditions, with a room square error of 0.28 and SNR of 7 dB. LoMauro *et al.* (2022) introduced a semi-automatic, robust pre-processing for respiratory data analysis using functional data analysis (FDA) techniques. The approach involved separating, detecting outliers based on time-duration, amplitude, and shape, and clustering breaths using K-medoids for different breathing patterns. The proposed methodology showed an error rate of less than 5 % for minimum detection and outlier removal.

Chauhan *et al.* (2017) developed a framework that combines smartphone acoustic sensors to identify breathing phases and estimate biomarkers. Breathing data was collected from pulmonary patients and healthy individuals using Samsung Galaxy Note 8 smartphones, chest bands, and spirometers. The system achieved 77.33 % accuracy and over 90 % accuracy in estimating respiratory rate and other biomarkers. Shih *et al.* (2019) developed a real-time breathing detection algorithm with low latency, running on a smartphone. To train and evaluate the developed system over 2.76 million breathing sounds from 43 participants was captured, and the system achieved 75.5 % accuracy in detecting breathing phases using a combination of attention-based LSTM models and CNN-based extraction modules. Wang *et al.* (2018) used a correlation-based frequency-modulated continuous wave (C-FMCW) approach for monitoring human breathing via audio signals. The common speaker and microphone components found in most homes were used. The system accurately identified subjects' respiration in a variety of environments, including different rooms and subject sleep positions. Khodaie *et al.* (2021) developed a system that records respiratory sounds from the upper airways using microphones implanted in a breathing mask. The study discovered a strong correlation (coefficient of 0.9) between acoustic features of respiratory sounds and respiratory metrics such as the peak flow and average flow.

Fang *et al.* (2023) proposed the identity-based respiration monitoring system for digital twins enabled healthcare (IDRes). The respiration rate was estimated by tracing the changes in the phase of the sonar signal and detecting the doppler frequency shift to capture chest motion characteristics. Experimental results showed 93.3 % recognition accuracy and the mean detection error of 0.49 bpm.

Xu *et al.* (2020) proposed the BreathListener, a system that monitors breathing in driving scenarios using audio devices on smartphones. The method captured fine-grained breathing waveforms in driving scenarios. The device used the energy spectrum density (ESD) of acoustic waves to record breathing processes in driving conditions. BreathListener used background removal and variational mode decomposition (VMD) to remove interference from driving settings while extracting the breathing pattern from the ESD signals. The retrieved breathing pattern was then translated into the Hilbert spectrum, and the fine-grained breathing waveform was generated using a deep learning architecture, based on generative adversarial networks. Chara *et al.* (2023) developed an FMCW-based acoustic system on a smartphone by emitting and receiving high-frequency chirps, the phone tracks tiny chest displacements. In trials this approach achieved extremely high accuracy – a median breathing-rate error below 0.15 breaths per minutes across various conditions. A smartphone-based contact method. Phokela *et al.* (2020) used a headset microphone under the nose to record nasal airflow sounds: it achieved respiration-rate errors less than 10 % even in noisy environments, demonstrating feasibility for home use.

Nemcova *et al.* (2020) estimated the heart rate, blood oxygen saturation (SpO2), and blood pressure (BP) using smartphone sensors. HR and SpO2 were determined by generating a photoplethysmogram (PPG) from the camera data, while BP was measured by calculating the pulse transit time value from the PPG and recording a phonocardiogram (PCG) via the microphone. The results showed mean absolute errors (MAE) of 1.1 % for SpO2 and 1.4 bpm for heart rate. Vincent *et al.* (2023) presented a multi-target blind source separation technique based on a single sonar. The use of the freqency hopping (FH) technique within the ULCW (Ultra-CW) scheme helped to minimize the effects of frequency-selective fading (FSF) and intersymbol interference (ISI) in the baseband, thereby improving the accuracy of acoustic signal transmission. The combination of continuous wave (CW) and FMCW signals in the ULCW scheme enhanced the transmission of energy from the smartphone, enabling accurate acoustic signal propagation over long distances. Doheny *et al.* (2023) developed a method to predict respiratory rate and exhale length from smartphone captured audio data. The method required calculation of the audio signal's basic frequency and detection of individual exhales with adaptive thresholding. Exhale boundary timings were optimised with adaptive physiological thresholds. The respiratory rate was determined by identifying peaks and troughs in the respiratory inductance plethysmography (RIP) signal, and exhale durations were calculated as the time between each peak and the next dip in the RIP signal. The RIP respiratory rate was utilised as the standard against which the audio respiratory rate was measured. The fundamental frequency of the respiration envelope was found as the frequency corresponding to the first peak in the harmonic product spectrum above 0.09 Hz. Other active acoustic methods use smart speakers to monitor breathing or heart rate, though these are mostly prototypes or proof-of-concept. The advantage of these non-contact methods is comfort and convenience and suitability for home or telehealth. However, they require a device (smartphone or speaker) close to the subject and can be sensitive to environmental noise or interference. Thick clothing, bedding, or a distance beyond 2 m–3 m can degrade signal, so practical use often means limiting the scenario.

7. Hardware based methods

This section examines approaches that incorporated hardware components, whether handheld or not, with the capability to determine the respiration rate of subjects.

Al-Ali and Lee (2012) patented a physiological acoustic monitoring system that collects physiological data from an acoustic sensor and generates respiration-related parameters in both real-time and non-real time. The system processes data by downsampling to provide raw audio of breathing sounds, and compresses it for futher analysis. Wang *et al.* (2023) presented the MultiResp, a multi-user respiration monitoring system that detects chest movement using acoustic signals. The system captures acoustic signals reflected from participants' chests, allowing for robust respiration monitoring even when subjects are facing away from the transceiver or blocked by barriers. MultiResp extracted fine-grained breath rate and phase differences between participants to differentiate breath waves with similar rates and adjust to dynamic variations in the number of monitored subjects. However, MultiResp fails when the sound pressure is less than 55 dB or when there is body movement which causes significant alterations in the multipath signals, causing erratic fluctuation of the channel impulse response (CIR).

Abbasi-Kesbi *et al.* (2018) presented a wireless acoustic sensor that used a phonocardiogram to detect heartbeat and respiratory rate. The system comprises a processor, transceiver, and two capacitor microphones for capturing heartbeat and respiration rate. The technology also measures breathing rate with a capacitor microphone placed near the mouth. The wireless acoustic sensor demonstrated high accuracy in predicting heartbeat and breathing rate, with RMSEs of less then 2.27 beats/min and 0.92 breaths/min, and standard deviations of less then 1.26 and 0.63, respectively. The system's sensitivity and specificity in recognizing PCG sounds ranged for S1 to S4 at 98.1 % and 98.3 %, respectively, representing a 3 % improvement over earlier work. This method accurately recorded heart and respiration rate in a variety of circumstances, including resting and breath-holding, with consistent results across numerous volunteers.

Wan *et al.* (2023) introduced a continuous multi-user respiratory tracking system designed for household settings using acoustic based commercial off-the-shelf (COTS) sensors. The system employed multi-stage algorithm to isolate and recombine respiration data from different paths to calculate the respiration rate of several moving persons. By utilizing features from multiple dimensions to distinguish between users in the same region, and applying Zadoff–Chu (ZC) sequences with optimal auto-correlation, it differentiates user pathways. The system transmits the ZC sequence modulated by a sinusoidal carrier as the transmitted sound signal, with its detection range and bandwidth determined by the length of the ZC sequence and frame length. The experimental results showed that RespTracker's two-stage algorithm can differentiate the respiratory pattern of at least four subjects over a three-meter distance.

8. Artificial intelligence based method

This section reviews studies that have adopted ML techniques using a microphone as the primary signal acquisition method. Figure 3 illustrates ML-based method.

Xie *et al.* (2023) utilised an autoencoder (AE) neural network to quantify the residual between the original and reconstructed signals, which can increase the end-to-end (e2e) respiration monitoring accuracy by a factor of 2.75 when compared to the baseline. Their approach employed deep learning techniques, combining an autoencoder neural network and a self-supervised learning to quantify signal quality. The use of radio frequency quality (RF-Q) further enhanced respiration monitoring accuracy. However, large volumes of training data are required for deep learning algorithms and the need for manual labelling, as training datasets for DL techniques is typically not publicly available.

Liu *et al.* (2021) proposed a reverberation aware network (RAN) algorithm for improving the robustness of DOA estimation. The algorithm used the beam cross-correlation (BCC) as an input to a deep neural network (DNN), explicitly characterizing reverber-

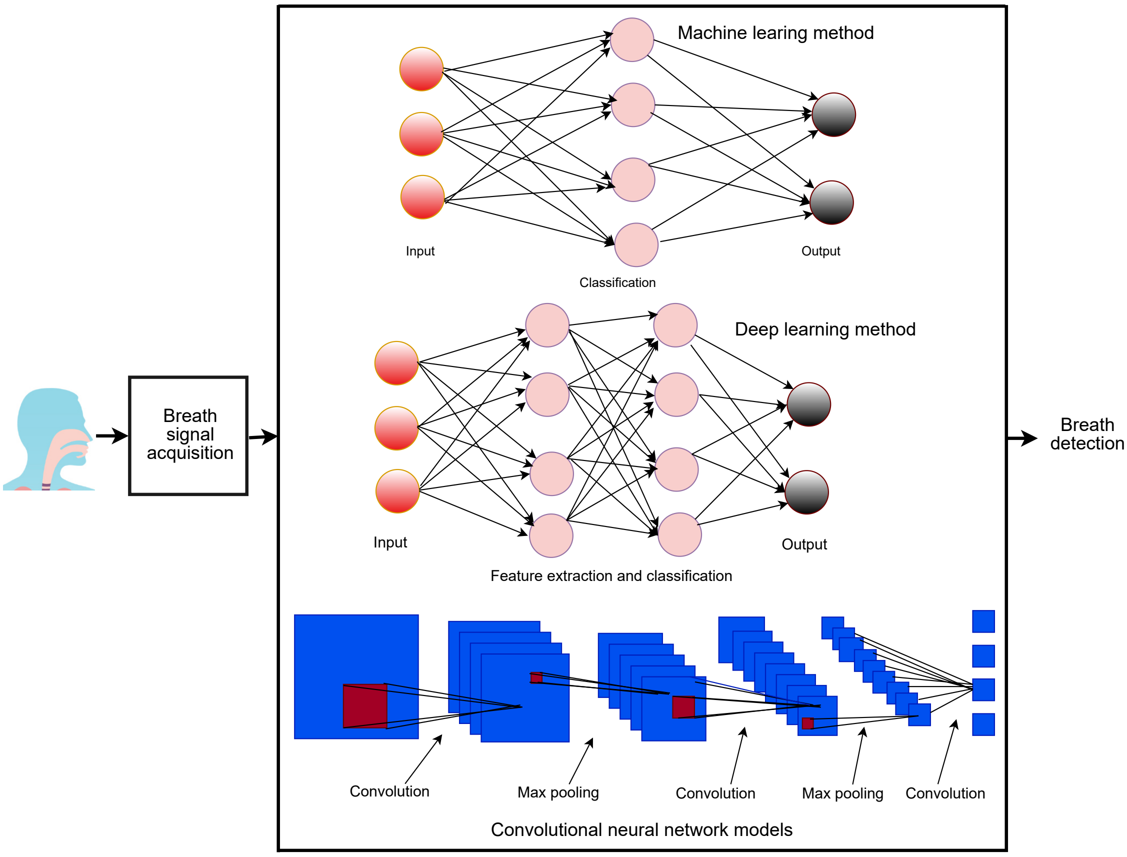

Fig. 3. Machine learning based method.

ation in the captured speech signal. The classic beamforming algorithm was used to generate beamforming outputs, the observed signals, which was then used as a reference for reverberation identification. The filter-sum (FS) beamforming algorithm was adopted for beamforming processing. Numerical simulations were based on virtual room environments generated with a reverberation model, as well as practical experiments under physical room environments, to evaluate the performance of the proposed method. The impact of different environments on the performance was evaluated by conducting experiments with different noise levels and source distances. In addition to the aforementioned research, some studies have also combined two methods, such as beamforming with ML (Zhang *et al.*, 2024) and smartphone with ML (Kavsaoğlu, Sehirli, 2023; Shih *et al.*, 2019; Xu *et al.*, 2020). Despite the promising application of ML in different fields, this area is underexplored especially when using a microphone as the non-contact health monitoring method.

9. Challenges and solution

Using microphones for signal acquisition in medical applications presents several challenges, with noise and interference being the most significant. To address these issues, some techniques have been proposed, including the use of adaptive noise reduction algorithms (Abed *et al.*, 2022; Thomsen, Du, 2020; Meyer *et al.*, 2020; Wu *et al.*, 2020; Wang, Qiu, 2020), directional microphones (Fischer, Puder, 2012; Kanamori, Terada, 2016; Nongpiur, 2018; Park *et al.*, 2020), and the application of ML (Jain, Hera, 2019; Shiozawa *et al.*, 2020; Takenaka, Ozawa, 2022). While these three methods have been independently used in the literature, this review suggests an integrated method that combines these approaches. In this proposed solution, adaptive noise reduction reduces inherent noise from recordings, directional microphones capture signals from a single direction or a patient, and ML processes the signals to minimize noise interference more effectively. Another challenge is the urgency with which some respiratory data are required to make informed decisions. High latency or processing delays can be problematic, this issue can be addressed by using edge computing, which processes data locally, or by employing optimized algorithms for real-time data processing. These suggested methods can significantly improve the responsiveness and reliability of microphone-based non-contact monitoring systems in medical applications. Apart from the above, other challenges with microphone include privacy, data security and technical implementation. Although data privacy and security were not mentioned by some of the articles reviewed. However, they remain one of the challenges associated with the use of microphones and other audio-based signal acquisition methods. Audio recordings should be treated with utmost security, as they reveal sensitive health information. Alqudaihi *et al.* (2021) suggested that only numeric features should be extracted from heart and respiratory signals and that data transmission should be anonymized summaries. To further enhance data privacy and security. Alqudaihi *et al.* (2021) also recommended implementing blockchain-based audit logs or federated learning techniques. Future directions could focus on the development of specialized contact microphones and the adoption of AI-based denoising and data encryption algorithms to improve the reliability and security of microphone-based monitoring systems. Moreover, privacy-preserving hardware innovations, such as MicPro proposed by Xiao *et al.* (2023) alongside the end-to-end encryption protocol used in some social media messaging applications – can address these issues adequately. Overall, research into the suggested solutions could enhance the performance of microphones as vital sign monitoring systems.

10. Conclusion

This review has presented the potential of microphone-based systems for non-contact sign monitoring. The transition from simple acoustic sensors to the adoption of intelligent health monitoring was made possible by technologies such as beamforming, ML, and smartphone integration. These systems have evolved from simple signal-capturing devices to sophisticated devices capable of detecting complex physiological patterns. Non-contact health monitoring systems can leverage these innovations, such as the integration of deep learning algorithms like CNN, RNN, or LSTM (Acharya, Basu, 2020; Thakur *et al.*, 2022). Although some research has been done in this area, the accuracy and real-time application of ML-based methods can be further improved through enhanced data collection processes, hybrid deep learning models, better feature extraction methods, and the use of microphone arrays instead of single microphones. Future directions could also focus on leveraging smartphone-based applications and cloud-based platforms to improve access, accuracy, and reliability while addressing other challenges associated with microphone-based systems.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contributions

Abiodun Ernest Amoran conceptualized the study and wrote the original draft; Dariusz Bismor supervised the research, provided guidance, and reviewed the manuscript. All authors reviewed and approved the final manuscript.

References

1. Aarts R.M. (2019), Acoustical patient monitoring using a sound classifier and a microphone, US Patent 10,269,228.
2. Abbasi-Kesbi R., Valipour A., Imani K. (2018), Cardiorespiratory system monitoring using a developed acoustic sensor, *Healthcare Technology Letters*, **5**(1): 7–12, https://doi.org/10.1049/htl.2017.0012.
3. Abed A., Cordon E., Warren N., Sanders D., Patel M., Liya D. (2022), Digital microphone with reduced processing noise, US Patent 11,438,682.
4. Acharya J., Basu A. (2020), Deep neural network for respiratory sound classification in wearable devices enabled by patient specific model tuning, *IEEE Transactions on Biomedical Circuits and Systems*, **14**(3): 535–544, https://doi.org/10.1109/TBCAS.2020.2981172.
5. Al-Ali A., Lee S.U.K. (2012), Physiological acoustic monitoring system, US Patent App. 13/675,014, https://patentscope.wipo.int/search/en/detail.jsf?docId=WO2013056141.
6. Alexandridis A., Mouchtaris A. (2017), Multiple sound source location estimation in wireless acoustic sensor networks using DOA estimates: The data-association problem, *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, **26**(2): 342–356, https://doi.org/10.1109/TASLP.2017.2772831.
7. Alqudaihi K.S. *et al.* (2021), Cough sound detection and diagnosis using artificial intelligence techniques: Challenges and opportunities, *IEEE Access*, **9**: 102327–102344, https://doi.org/10.1109/ACCESS.2021.3097559.
8. Arenas-Garcia J., Azpicueta-Ruiz L.A., Silva M.T.M., Nascimento V.H., Sayed A.H. (2021), Combinations of adaptive filters: Performance and convergence properties, *IEEE Signal Processing Magazine*, **33**: 120–140, https://doi.org/10.1109/MSP.2015.2481746.
9. Artemyev M., Churikova M., Grinenko M., Perepelkina O. (2020), Robust algorithm for remote photoplethysmography in realistic conditions, *Digital Signal Processing*, **104**: 102737, https://doi.org/10.1016/j.dsp.2020.102737.

10. Ashraf W., Moussavi Z. (2024), Design and analysis of a contact piezo microphone for recording tracheal breathing sounds, *Sensors*, **24**(17): 5511, https://doi.org/10.3390/s24175511.

11. Atkins A., Cohen I., Benesty J. (2021), Adaptive line enhancer for nonstationary harmonic noise reduction, *Computer Speech and Language*, **70**: 101245, https://doi.org/10.1016/j.csl.2021.101245.

12. Barany L.P. (1993), Ultrasonic non-contact motion monitoring system, US Patent 5,220,922.

13. Balgemann T.W., Pedersen S.C., Pessin J.M., Shumard B.R., Sutter L.L., Perkofski R.J. (2023), Microphone with adjustable signal processing, US Patent App. 18/197,416.

14. Beckmann P. (2017), How digital signal processing can enhance the utility and performance of microphones, https://21088554.fs1.hubspotusercontent-na1.net/hubfs/21088554/digital_microphone_processing_paper%20(1).pdf (access: 29.05.2024).

15. Boccignone G., D'Amelio A., Ghezzi O., Grossi G., Lanzarotti R. (2023), An evaluation of non-contact photoplethysmography-based methods for remote respiratory rate estimation, *Sensors*, **23**(7): 3387, https://doi.org/10.3390/s23073387.

16. Branson R.D., Rodriquez D. Jr. (2023), COVID-19 lessons learned: Response to the anticipated ventilator shortage, *Respiratory Care*, **68**(1): 129–150, https://doi.org/10.4187/respcare.10676.

17. Celik N., Gagarin R., Youn H., Iskander M.F. (2011), A noninvasive microwave sensor and signal processing technique for continuous monitoring of vital signs, *IEEE Antennas and Wireless Propagation Letters*, **10**: 286–289, https://doi.org/10.1109/LAWP.2011.2132690.

18. Chara A., Zhao T., Wang X., Mao S. (2023), Respiratory biofeedback using acoustic sensing with smartphones, *Smart Health*, **28**: 100387, https://doi.org/10.1016/j.smhl.2023.100387.

19. Chauhan J., Hu Y., Seneviratne S., Misra A., Seneviratne A., Lee Y. (2017), BreathPrint: Breathing acoustics-based user authentication, [in:] *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*, pp. 278–291, https://doi.org/10.1145/3081333.3081355.

20. Chen Z., Li Z., Wang S., Yin F. (2015), A microphone position calibration method based on combination of acoustic energy decay model and TDOA for distributed microphone array, *Applied Acoustics*, **95**: 13–19, https://doi.org/10.1016/j.apacoust.2015.02.013.

21. Dafna E., Rosenwein T., Tarasiuk A., Zigel Y. (2015), Breathing rate estimation during sleep using audio signal analysis, [in:] *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5981–5984, https://doi.org/10.1109/EMBC.2015.7319754.

22. Dei D. *et al.* (2009), Non-contact detection of breathing using a microwave sensor, *Sensors*, **9**(4): 2574–2585, https://doi.org/10.3390/s90402574.

23. Dey N., Ashour A.S. (2018), *Direction of Arrival Estimation and Localization of Multi-Speech Sources*, Springer, https://doi.org/10.1007/978-3-319-73059-2.

24. Doclo S., Kellermann W., Makino S., Nordholm S.E. (2015), Multichannel signal enhancement algorithms for assisted listening devices: Exploiting spatial diversity using multiple microphones, *IEEE Signal Processing Magazine*, **32**(2): 18–30, https://doi.org/10.1109/MSP.2014.2366780.

25. Doheny E.P. *et al.* (2023), Estimation of respiratory rate and exhale duration using audio signals recorded by smartphone microphones, *Biomedical Signal Processing and Control*, **80**(Part 1): 104318, https://doi.org/10.1016/j.bspc.2022.104318.

26. Doyle D.J. (2019), Acoustical respiratory monitoring in the time domain, *The Open Anesthesia Journal*, **13**, https://doi.org/10.2174/2589645801913010144.

27. Edanami K. *et al.* (2022), Remote sensing of vital signs by medical radar time-series signal using cardiac peak extraction and adaptive peak detection algorithm: Performance validation on healthy adults and application to neonatal monitoring at an NICU, *Computer Methods and Programs in Biomedicine*, **226**: 107163, https://doi.org/10.1016/j.cmpb.2022.107163.

28. Fang B., Lane N.D., Zhang M., Boran A., Kawsar F. (2016), BodyScan: Enabling radio-based sensing on wearable devices for contactless activity and vital sign monitoring, [in:] *Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services*, pp. 97–110, http://doi.org/10.1145/2906388.2906411.

29. Fang K. *et al.* (2023), IDRes: Identity-based respiration monitoring system for digital twins enabled healthcare, *IEEE Journal on Selected Areas in Communications*, **41**(10): 3333–3348, https://doi.org/10.1109/JSAC.2023.3310095.

30. Ferrante G., Licari A., Marseglia G., La Grutta S. (2020), Artificial intelligence as an emerging diagnostic approach in paediatric pulmonology, *Respirology*, **25**(10): 1029–1030, https://doi.org/10.1111/resp.13842.

31. Fischer E., Puder H. (2012), Method for reducing interferences of a directional microphone, US Patent 8,135,142.

32. Fraden J. (2014), Non-contact medical thermometer with stray radiation shielding, US Patent 8,834,019.

33. Fukuda T., Watanabe S., Matsumoto H., Tsuji H. (2018), Microphone array, monitoring system, and sound pickup setting method, US Patent 9,860,635.

34. Garzotto F. *et al.* (2020), COVID-19: Ensuring our medical equipment can meet the challenge, *Expert Review of Medical Devices*, **17**(6): 483–489, https://doi.org/10.1080/17434440.2020.1772757.

35. Genova J.J. (1997), Non-invasive medical monitor system, US Patent 5,590,650.

36. Gupta P., Wen H., Di Francesco L., Ayazi F. (2021), Detection of pathological mechano-acoustic signatures using precision accelerometer contact microphones in patients with pulmonary disorders, *Scientific Reports*, **11**(1): 13427, https://doi.org/10.1038/s41598-021-92666-2.

37. Haase W.C., Haase Z.S., Young R.F., Monin P.E., McCarthy C.W., Sarles F.W. (2011), Non-contact biometric monitor, US Patent App. 13/034,394.

38. Hall T. *et al.* (2015), A phased array non-contact vital signs sensor with automatic beam steering, [in:] *2015 IEEE MTT-S International Microwave Symposium*, pp. 1–4, https://doi.org/10.1109/MWSYM.2015.7166973.

39. Han L. *et al.* (2023), Health monitoring via heart, breath, and Korotkoff sounds by wearable piezoelectret patches, *Advanced Science*, **10**(28): 2301180, https://doi.org/10.1002/advs.202301180.

40. Hashim H.A., Ahmed N.M., Shabeeb A.G. (2023), Infant heart rate estimation based on non-contact UV photoplethysmography, *Indonesian Journal of Electrical Engineering and Computer Science*, **31**(1): 180–188, http://doi.org/10.11591/ijeecs.v31.i1.pp180-188.

41. Henry M. (2023), An ultra-precise fast Fourier transform, *Measurement*, **220**: 113372, https://doi.org/10.1016/j.measurement.2023.113372.

42. Hoctor R.T., Thomenius K.E., Dentinger A.M. (2008), Method and apparatus for ultrasonic continuous, non-invasive blood pressure monitoring, US Patent 7,425,199.

43. Hsu G.-S.J., Xie R.-C., Ambikapathi A.M., Chou K.-J. (2020), A deep learning framework for heart rate estimation from facial videos, *Neurocomputing*, **417**: 155–166, https://doi.org/10.1016/j.neucom.2020.07.012.

44. Huang B., Lin C.-L., Chen W., Juang C.-F., Wu X. (2021), A novel one-stage framework for visual pulse rate estimation using deep neural networks, *Biomedical Signal Processing and Control*, **66**: 102387, https://doi.org/10.1016/j.bspc.2020.102387.

45. Ipenza S.C., Masiero B.S. (2018), Microphone array processing of pulse-density modulated bitstreams, [in:] *28th Meeting of the Brazilian Acoustics Society October 3 to 5, 2018, Porto Alegre – RS*, **6**: 7, https://doi.org/10.17648/sobrac-87156.

46. Islam B. *et al.* (2021), BreathTrack: Detecting regular breathing phases from unannotated acoustic data captured by a smartphone, [in:] *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, **5**(3): 1–22, https://doi.org/10.1145/3478123.

47. Islam S.M.M., Yavari E., Rahman A., Lubecke V.M., Boric-Lubecke O. (2019), Multiple subject respiratory pattern recognition and estimation of direction of arrival using phase-comparison monopulse radar, [in:] *2019 IEEE Radio and Wireless Symposium (RWS)*, pp. 1–4, https://doi.org/10.1109/RWS.2019.8714272.

48. Jahanshahi P., Wei Q., Jie Z., Zalnezhad E. (2018), Designing a non-invasive surface acoustic resonator for ultra-high sensitive ethanol detection for an on-the-spot health monitoring system, *Biotechnology and Bioprocess Engineering*, **23**: 394–404, https://doi.org/10.1007/s12257-017-0432-5.

49. Jain A.D., Hera C.M. (2019), Noise reduction using machine learning, Patent No. 10,580,430, https://patents.google.com/patent/WO2019079713A1/fr.

50. Joshi M., Moadi A.-K., Theilmann P., Fathy A.E. (2023), Compact millimeter wave radar for vital sign detection: A comprehensive study, [in:] *2023 16th International Conference on Advanced Technologies, Systems and Services in Telecommunications (TELSIKS)*, pp. 114–117, https://doi.org/10.1109/TELSIKS57806.2023.10316015.

51. Kanamori T., Terada Y. (2016), Directional microphone device, acoustic signal processing method, and program, US Patent 9,264,797.

52. Katoh M., Kanazawa T., Abe Y., Sun G., Matsui T. (2023), Development of a non-contact 15-second paediatric respiratory rate monitor using microwave radar and its clinical application, *Acta Paediatrica*, **112**(3): 493–495, https://doi.org/10.1111/apa.16585.

53. Kavsaoğlu A.R., Sehirli E. (2023), A novel study to classify breath inhalation and breath exhalation using audio signals from heart and trachea, *Biomedical Signal Processing and Control*, **80**(Part 1): 104220, https://doi.org/10.1016/j.bspc.2022.104220.

54. Khatkhate A.M., Raut V., Jadhav M., Alva S., Vichare K., Nadkarni A. (2022), Identification of basic respiratory patterns for disease-related symptoms through a microphone device, *Journal of Engineering Research and Sciences*, **1**(6): 36–44, https://doi.org/10.55708/js0106005.

55. Khodaie M., Nafisi V.R., Moghadam F.F. (2021), Design and implementation of an apparatus for respiratory parameters estimation based on acoustic methods, [in:] *2021 28th National and 6th International Iranian Conference on Biomedical Engineering (ICBME)*, pp. 15–21, https://doi.org/10.1109/ICBME54433.2021.9750286.

56. Khong W.L., Mariappan M. (2019), The evolution of heart beat rate measurement techniques from contact based photoplethysmography to non-contact based photoplethysmography imaging, [in:] *2019 IEEE International Circuits and Systems Symposium (ICSyS)*, pp. 1–4, https://doi.org/10.1109/ICSyS47076.2019.8982534.

57. Kranjec J., Beguš S., Geršak G., Drnovšek J. (2014), Non-contact heart rate and heart rate variability measurements: A review, *Biomedical Signal Processing and Control*, **13**: 102–112, https://doi.org/10.1016/j.bspc.2014.03.004.

58. Lee C.S., Li M., Lou Y., Abbasi Q.H., Imran M. (2023), An acoustic system of sound acquisition and

image generation for frequent and reliable lung function assessment, *IEEE Sensors Journal*, **24**(3): 3731–3747, https://doi.org/10.1109/JSEN.2023.3344136.

59. Levy A., Gannot S., Habets E.A.P. (2010), Multiple-hypothesis extended particle filter for acoustic source localization in reverberant environments, *IEEE Transactions on Audio, Speech, and Language Processing*, **19**(6): 1540–1555, https://doi.org/10.1109/TASL.2010.2093517.
60. Li C., Qian Q. (2024), A deep learning-based animation video image data anomaly detection and recognition algorithm, *Journal of Organizational and End User Computing (JOEUC)*, **36**(1): 1–25, https://doi.org/10.4018/JOEUC.345929.
61. Liang H. *et al.* (2023), Wearable and multifunctional self-mixing microfiber sensor for human health monitoring, *IEEE Sensors Journal*, **23**(3): 2122–2127, https://doi.org/10.1109/JSEN.2022.3225196.
62. Liu J., Li D., Wang L., Zhang F., Xiong J. (2022), Enabling contact-free acoustic sensing under device motion, [in:] *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, **6**(3): 128, https://doi.org/10.1145/3550329.
63. Liu Y., Tong F., Zhong S., Hong Q., Li L. (2021), Reverberation aware deep learning for environment tolerant microphone array DOA estimation, *Applied Acoustics*, **184**: 108337, https://doi.org/10.1016/j.apacoust.2021.108337.
64. Llorca-Bofi J., Heck J., Dreier C., Vorlaender M. (2024), Urban background sound recordings for virtual acoustics under various weather conditions, *The Journal of the Acoustical Society of America*, **155**(3_Supplement): A178, https://doi.org/10.1121/10.0027230.
65. LoMauro A., Colli A., Colombo L., Aliverti A. (2022), Breathing patterns recognition: A functional data analysis approach, *Computer Methods and Programs in Biomedicine*, **217**: 106670, https://doi.org/10.1016/j.cmpb.2022.106670.
66. Lv W., He W., Lin X., Miao J. (2021), Non-contact monitoring of human vital signs using FMCW millimeter wave radar in the 120 GHz band, *Sensors*, **21**(8): 2732, https://doi.org/10.3390/s21082732.
67. Lyu W., Chen S., Tan F., Yu C. (2022), Vital signs monitoring based on interferometric fiber optic sensors, *Photonics*, **9**(2): 50, https://doi.org/10.3390/photonics9020050.
68. Massaroni C., Nicolò A., Sacchetti M., Schena E. (2021), Contactless methods for measuring respiratory rate: A review, *IEEE Sensors Journal*, **21**(11): 12821–12839, https://doi.org/10.1109/JSEN.2020.3023486.
69. Mathworks (n.d.), *Conventional and adaptive beamformer*, https://www.mathworks.com/help/phased/ug/conventional-and-adaptive-beamformers.html (access: 4.06.2024).
70. Mercuri M. *et al.* (2018), A direct phase-tracking Doppler radar using wavelet independent component analysis for non-contact respiratory and heart rate monitoring, *IEEE Transactions on Biomedical Circuits and Systems*, **12**(3): 632–643, https://doi.org/10.1109/TBCAS.2018.2813013.
71. Meyer P., Elshamy S., Fingscheidt T. (2020), Multichannel speaker interference reduction using frequency domain adaptive filtering, *EURASIP Journal on Audio, Speech, and Music Processing*, **2020**: 14, https://doi.org/10.1186/S13636-020-00180-6.
72. Nemcova A. *et al.* (2020), Monitoring of heart rate, blood oxygen saturation, and blood pressure using a smartphone, *Biomedical Signal Processing and Control*, **59**: 101928, https://doi.org/10.1016/j.bspc.2020.101928.
73. Nongpiur R.C. (2018), Directional microphone device and signal processing techniques, Patent.
74. Okamoto Y., Nguyen T.-V., Takahashi H., Takei Y., Okada H., Ichiki M. (2023), Highly sensitive low-frequency-detectable acoustic sensor using a piezoresistive cantilever for health monitoring applications, *Scientific Reports*, **13**(1): 6503, https://doi.org/10.1038/s41598-023-33568-3.
75. Open Music Lab (2022), *Electret microphones*, http://www.openmusiclabs.com/learning/sensors/electret-microphones/index.html (access: 1.06.2024).
76. Orlandic L., Teijeiro T., Alonso D.A. (2021), The COUGHVID crowdsourcing dataset, a corpus for the study of large-scale cough analysis algorithms, *Scientific Data*, **8**: 156, https://doi.org/10.1038/s41597-021-00937-4.
77. Park D.Y., Lim H.Y., Min C.K. (2020), Directional microphone device, Patent.
78. Paul V.-S., Hahn N., Hollebon J. (2023), Extraction of ambience sound from microphone array recordings for spatialisation, [in:] *2023 Immersive and 3D Audio: From Architecture to Automotive (I3DA)*, https://doi.org/10.1109/I3DA57090.2023.10289397.
79. Phokela K.K., Naik V. (2020), Use of smartphone's headset microphone to estimate the rate of respiration, [in:] *2020 International Conference on COMmunication Systems & NETworkS (COMSNETS)*, pp. 64–69, https://doi.org/10.1109/COMSNETS48256.2020.9027297.
80. Picchio R. *et al.* (2019), Comparing accuracy of three methods based on the GIS environment for determining winching areas, *Electronics*, **8**(1): 53, https://doi.org/10.3390/electronics8010053.
81. Pramono R.X.A., Imtiaz S., Rodriguez-Villegas E. (2019), Evaluation of features for classification of wheezes and normal respiratory sounds, *PLoS ONE*, **14**(3): e0213659, https://doi.org/10.1371/journal.pone.0213659.
82. PreSonus (2022), *What is a condenser microphone*, https://www.presonus.com/blogs/technical/what-is-a-condenser-microphone? (access: 1.06.2024).
83. Qian K., Wu C., Xiao F., Zheng Y., Zhang Y., Yang Z., Liu Y. (2018), Acousticcardiogram: Monitoring heartbeats using acoustic signals on smart

devices, [in:] *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*, pp. 1574–1582, https://doi.org/10.1109/INFOCOM.2018.8485978.

84. Rangayyan R.M. [Ed.] (2015), Frequency domain characterization of signals and systems, [in:] *Biomedical Signal Analysis*, Wiley, pp. 349–395, https://doi.org/10.1002/9781119068129.ch6.

85. Renjini A., Swapna M.S., Raj V., Sankararaman S. (2021), Graph-based feature extraction and classification of wet and dry cough signals: A machine learning approach, *Journal of Complex Networks*, **9**(6): cnab039, https://doi.org/10.1093/comnet/cnab039.

86. Rose B. (2022), *An introduction to MEMS microphone arrays*, https://www.sameskydevices.com/blog/an-introduction-to-mems-microphone-arrays (access: 31.05.2024).

87. Roseline S.A., Saraf K., Sruti I.N.V.D. (2024), Intelligent human anomaly detection using LSTM autoencoders, [in:] *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, pp. 1–7, https://doi.org/10.1109/ACCAI61061.2024.10602454.

88. Ryu J., Hong S., Liang S., Pak S., Chen Q., Yan S. (2021), A measurement of illumination variation-resistant noncontact heart rate based on the combination of singular spectrum analysis and sub-band method, *Computer Methods and Programs in Biomedicine*, **200**: 105824, https://doi.org/10.1016/j.cmpb.2020.105824.

89. Sabokrou M., Pourreza M., Li X., Fathy M., Zhao G. (2021), Deep-HR: Fast heart rate estimation from face video under realistic conditions, *Expert Systems with Applications*, **186**: 115596, https://doi.org/10.1016/j.eswa.2021.115596.

90. Sakamoto T., Yamashita K. (2019), Noncontact measurement of autonomic nervous system activities based on heart rate variability using ultra-wideband array radar, *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, **4**(3): 208–215, https://doi.org/10.1109/JERM.2019.2948827.

91. Savazzi S., Rampa V., Costa L., Kianoush S., Tolochenko D. (2020), Processing of body-induced thermal signatures for physical distancing and temperature screening, *IEEE Sensors Journal*, **21**(13): 14168–14179, https://doi.org/10.1109/JSEN.2020.30 47143.

92. Sharma P., Imtiaz S.A., Rodriguez-Villegas E. (2019), Acoustic sensing as a novel wearable approach for cardiac monitoring at the wrist, *Scientific Reports*, **9**: 20079, https://doi.org/10.1038/s41598-019-55599-5.

93. Shih C., Tomita N., Lukic Y.X., Reguera Á.H., Fleisch E., Kowatsch T. (2019), Breeze: Smartphone-based acoustic real-time detection of breathing phases for a gamified biofeedback breathing training, [in:] *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, **3**(4): 1–30, https://doi.org/10.1145/3369835.

94. Shiozawa K., Ozawa K., Ise T. (2020), Noise suppression using a differential-type microphone array and two-dimensional amplitude and phase spectra, [in:] *2020 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pp. 46–51.

95. Shokouhmand A., Eckstrom S., Gholami B., Tavassolian N. (2022), Camera-augmented non-contact vital sign monitoring in real time, *IEEE Sensors Journal*, **22**(12): 11965–11978, https://doi.org/10.1109/JSEN.2022.3172559.

96. Smithard J. *et al.* (2017), An advanced multi-sensor acousto-ultrasonic structural health monitoring system: Development and aerospace demonstration, *Materials*, **10**(7): 832, https://doi.org/10.3390/ma10070832.

97. Sun L., Luo C., Bai G., Gu C., Zhu X. (2022), Remote measurement of human breathing and heartbeat in large scene based on TX-RX joint beamforming, [in:] *2022 16th ICME International Conference on Complex Medical Engineering (CME)*, pp. 12–15, https://doi.org/10.1109/CME55444.2022.10063285.

98. Taghavirashidizadeh A., Sharifi F., Vahabi S.A., Hejazi A., SaghabTorbati M., Mohammed A.S. (2022), WTD-PSD: Presentation of novel feature extraction method based on discrete wavelet transformation and time-dependent power spectrum descriptors for diagnosis of Alzheimer's disease, *Computational Intelligence and Neuroscience*, **2022**: 9554768, https://doi.org/10.1155/2022/9554768.

99. Takenaka K., Ozawa K. (2022), Noise suppression system using deep learning for smart devices, [in:] *2022 IEEE 4th Global Conference on Life Sciences and Technologies (LifeTech)*, pp. 559–560, https://doi.org/10.1109/LifeTech53646.2022.9754759.

100. Taniguchi M., Kageyama T., Okamoto Y., Matsunaga T., Lee S.S. (2023), A vital sign monitoring system using a MEMS microphone for dog, [in:] *2023 IEEE 18th International Conference on Nano/Micro Engineered and Molecular Systems (NEMS)*, pp. 70–73, https://doi.org/10.1109/NEMS57332.2023.10190878.

101. Tashev I., Acero A. (2006), Microphone array post-processor using instantaneous direction of arrival, [in:] *Proceedings of International Workshop on Acoustic, Echo and Noise Control IWAENC 2006*, https://www.microsoft.com/en-us/research/publication/microphone-array-post-processor-using-instantaneous-direction-of-arrival/.

102. Thakur D., Biswas S., Ho E.S.L., Chattopadhyay S. (2022), ConvAE-LSTM: Convolutional autoencoder long short-term memory network for smartphone-based human activity recognition, *IEEE Access*, **10**: 4137–4156, https://doi.org/10.1109/ACCESS.2022.3140373.

103. Thomsen H., Du Y. (2020), Digital microphone noise attenuation, US Patent 10,559,293.

104. Thundat T.G., Oden P.I., Datskos P.G. (2000), Non-contact passive temperature measuring system and method of operation using micro-mechanical sensors, US Patent 6,050,722.

105. Toa M., Whitehead A. (2019), Ultrasonic sensing basics. Application note, *Texas Instruments*, https://www.ti.com/lit/an/slaa907d/slaa907d.pdf (access: 30.05.2025).
106. Tocci M. (2024), *Smartphone history and evolution*, Simple Texting, https://simpletexting.com/blog/where-have-we-come-since-the-first-smartphone/ (access: 3.04.2024).
107. Todorović D. *et al.* (2015), Multilayer graphene condenser microphone, *2D Materials*, **2**(4): 045013, https://doi.org/10.1088/2053-1583/2/4/045013.
108. Tran D., Duong K., Bhowmik U.K. (2014), A VHDL based controller design for non-contact temperature and breathing sensors suitable for crib, [in:] *2014 IEEE International Conference on Bioinformatics and Bioengineering*, 126–133, https://doi.org/10.1109/BIBE.2014.11.
109. Tsai T.C., Orav E.J., Jha A.K., Figueroa J.F. (2022), National estimates of increase in US mechanical ventilator supply during the COVID-19 pandemic, *JAMA Network Open*, **5**(8): e2224853, https://doi.org/10.1001/jamanetworkopen.2022.24853.
110. Valipour A., Abbasi-Kesbi R. (2017), A heartbeat and respiration rate sensor based on phonocardiogram for healthcare applications, [in:] *2017 Iranian Conference on Electrical Engineering (ICEE)*, pp. 45–48, https://doi.org/10.1109/IranianCEE.2017.7985502.
111. Vincent K., Wang L., Liu W. (2023), Towards one-to-many respiration monitoring via dual-mode acoustic signals, *IEEE Transactions on Consumer Electronics*, **70**(1): 2970–2978, https://doi.org/10.1109/TCE.2023.3321683.
112. Wahyu Y. *et al.* (2022), 24 GHz FMCW radar for non-contact respiratory detection, [in:] *2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, pp. 752–755, https://doi.org/ 10.1109/ICITISEE57756.2022.10057704.
113. Wan H., Shi S., Cao W., Wang W., Chen G. (2023), Multi-user room-scale respiration tracking using COTS acoustic devices, *ACM Transactions on Sensor Networks*, **19**(4): 85, https://doi.org/10.1145/3594220.
114. Wang G., Zhang C., Chen X., Ji X., Xue J., Wang H. (2020), Bi-stream pose-guided region ensemble network for fingertip localization from stereo images, *IEEE Transactions on Neural Networks and Learning Systems*, **31**(12): 5153–5165, https://doi.org/10.1109/TNNLS.2020.2964037.
115. Wang T. *et al.* (2023), *MultiResp*: Robust respiration monitoring for multiple users using acoustic signal, *IEEE Transactions on Mobile Computing*, **23**(5): 3785–3801, https://doi.org/10.1109/TMC.2023.3279976.
116. Wang T., Zhang D., Zheng Y., Gu T., Zhou X., Dorizzi B. (2018), C-FMCW based contactless respiration detection using acoustic signal, [in:] *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, **1**(4): 1–20, https://doi.org/10.1145/3161188.
117. Wang Y., Wang Z., Zhang J.A., Zhang H., Xu M. (2023), Vital sign monitoring in dynamic environment via mmWave radar and camera fusion, *IEEE Transactions on Mobile Computing*, **23**(5): 4163–4180, https://doi.org/10.1109/TMC.2023.3288850.
118. Wang Z., Qiu F. (2020), Voice signal noise reduction processing method, microphone and electronic equipment, Unified Patents, Patent No. CN-109065067-A.
119. Wang Z., Zhang F., Li S., Jin B. (2021), Exploiting passive beamforming of smart speakers to monitor human heartbeat in real time, [in:] *2021 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, https://doi.org/10.1109/GLOBECOM46510.2021.9685922.
120. Wu S., Wang W., Bian Y., Xu Z. (2020), Wind noise processing method, device, and system employing multiple microphones, and storage medium, Patent.
121. Xiao S., Ji X., Yan C., Zheng Z., Xu W. (2023), MicPro: Microphone-based voice privacy protection, [in:] *Proceedings of the 2023 ACM SIGSAC Conference on Computer and Communications Security*, pp. 1302–1316, https://doi.org/10.1145/3576915.3616616.
122. Xiao W., Yu L. (2021), Non-contact passive sensing of acoustic emission signal using the air-coupled transducer, *Health Monitoring of Structural and Biological Systems XV*, **11593**: 412–419, https://doi.org/10.1117/12.2583218.
123. Xie W., Tian R., Zhang J., Zhang Q. (2020), Noncontact respiration detection leveraging music and broadcast signals, *IEEE Internet of Things Journal*, **8**(4): 2931–2942, https://doi.org/10.1109/JIOT.2020.3021915.
124. Xie Z., Nederlander A., Park I., Ye F. (2023), Poster: Quantifying signal quality using autoencoder for robust RF-based respiration monitoring, [in:] *Proceedings of the 8th ACM/IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies*, pp. 187–188, https://doi.org/10.1145/3580252.3589999.
125. Xiong J., Hong H., Xiao L., Wang E., Zhu X. (2023), Vital signs detection with difference beamforming and orthogonal projection filter based on SIMO-FMCW radar, *IEEE Transactions on Microwave Theory and Techniques*, **71**(1): 83–92, https://doi.org/10.1109/TMTT.2022.3181129.
126. Xu W. *et al.* (2021), Unobtrusive vital signs and activity monitoring based on dual mode fiber, *Optical Fiber Technology*, **64**: 102530, https://doi.org/10.1016/j.yofte.2021.102530.
127. Xu W., Shen Y., Yu C., Dong B., Zhao W., Wang Y. (2020), Long modal interference in multimode fiber and its application in vital signs monitoring, *Optics Communications*, **474**: 126100, https://doi.org/10.1016/j.optcom.2020.126100.
128. Xu X., Yu J., Chen Y. (2022), Leveraging acoustic signals for fine-grained breathing monitoring in driving environments, *IEEE Transactions on Mobile Computing*, **21**(3): 1018–1033, https://doi.org/10.1109/TMC.2020.3015828.

129. Yang F., He S., Sadanand S., Yusuf A., Bolic M. (2022), Contactless measurement of vital signs using thermal and RGB cameras: A study of COVID-19-related health monitoring, *Sensors*, **22**(2): 627, https://doi.org/10.3390/s22020627.

130. Zakrzewski M. (2015), *Methods for Doppler Radar Monitoring of Physiological Signals*, Ph.D. Thesis, Tampere University of Technology, Finland, https://trepo.tuni.fi//handle/10024/114695.

131. Zhang G., Geng L., Xie F., He C.-D. (2024), A dynamic convolution-transformer neural network for multiple sound source localization based on functional beamforming, *Mechanical Systems and Signal Processing*, **211**: 111272, https://doi.org/10.1016/j.ymssp.2024.111272.

132. Zhang H. *et al.* (2023a), Radar-Beat: Contactless beat-by-beat heart rate monitoring for life scenes, *Biomedical Signal Processing and Control*, **86**(Part C): 105360, https://doi.org/10.1016/j.bspc.2023.105360.

133. Zhang X., Bao Z., Yin Y., Yang X., Xu X., Niu Q. (2023b), Finding potential pneumoconiosis patients with commercial acoustic device, [in:] *2023 IEEE Symposium on Computers and Communications (ISCC)*, pp. 310–315, https://doi.org/10.1109/ISCC58397.2023.10217963.

134. Zhao T., Fu X., Zhou Y., Zhan J., Chen K., Li Z. (2023), Noncontact monitoring of heart rate variability using a fiber optic sensor, *IEEE Internet of Things Journal,* **10**(17): 14988–14994, https://doi.org/10.1109/JIOT.2023.3262634.