Contactless Diseases Diagnoses Using Wireless Communication Sensing: Methods and Challenges Survey

NAJAH ABED ABU ALI, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE
MUBASHIR REHMAN, Department of Electrical and Computer Engineering, COMSATS University Islamabad, Attock, Pakistan
SHAHID MUMTAZ, Department of Engineering and the Department of Electronic Engineering, Nottingham Trent University, Nottingham, UK and the Department of Electronic Engineering, Kyung Hee University, Yongin-si, South Korea
MUHAMMAD BILAL KHAN, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE and Department of Electrical and Computer Engineering, COMSATS University Islamabad, Attock, Pakistan
MOHAMMAD HAYAJNEH, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE
FARMAN ULLAH, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE
RAZA ALI SHAH, Department of Electrical Engineering, HITEC University, Taxila, Pakistan

Respiratory illness diagnosis and continuous monitoring are becoming popular as sensitive markers of chronic diseases. This interest has motivated the increased development of respiratory illness diagnosis by exploiting wireless communication as a sensing system. Several methods for diagnosing a respiratory illness are based on multiple sensors and techniques. Depending on whether the device embeds the sensor in contact with the body or not, these techniques are commonly categorized as contact based or contactless. Contactless methods have gained increasing popularity due to their ubiquitous nature, non-intrusiveness, and low cost. However, contactless methods are difficult to implement, with several challenges such as dynamic wireless communication environments. This article comprehensively reviews all contactless respiratory illnesses using wireless communication sensing methods, their associated challenges, and issues. In addition,

This work was supported by the Big Data Analytics Center (UAEU grant G00003800) and Zayed Center for Health Sciences (UAEU grant G00003476).
Authors' addresses: N. A. Abu Ali, M. Hayajneh, and F. Ullah, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE; e-mails: najah@uaeu.ac.ae, mhayajneh@uaeu.ac.ae, farman@uaeu.ac.ae; M. Rehman, Department of Electrical and Computer Engineering, COMSATS University Islamabad, Attock, Pakistan; e-mail: mubashir_rehman7@ciit-attock.edu.pk; S. Mumtaz, Department of Engineering and the Department of Electronic Engineering, Nottingham Trent University, Nottingham, UK and the Department of Electronic Engineering, Kyung Hee University, Yongin-si, Gyeonggi-do 17104, South Korea; e-mail: dr.shahid.mumtaz@ieee.org; M. B. Khan, Department of Computer Engineering, College of IT, United Arab Emirates University, Al-Ain, UAE and Department of Electrical and Computer Engineering, COMSATS University Islamabad, Attock, Pakistan; e-mail: engr_tanoli@ciit-attock.edu.pk; R. A. Shah, Department of Electrical Engineering, HITEC University, Taxila, Pakistan; e-mail: raza.ali.shah@hitecuni.edu.pk.

ACM 0360-0300/2024/04-ART226
https://doi.org/10.1145/3648352

applications of respiratory illness diagnosis methods using wireless communication are provided to investigate each method's potential development and applicability. Continuous and accurate diagnosis of respiratory illness using wireless communication sensing systems can assist caregivers in enhancing the care quality and bestowing patients with more freedom for both inpatients and outpatients. Furthermore, wireless communication monitoring systems could lead to treatment plans remotely more effectively, decrease the duration of patient stays in medical facilities, and reduce overall treatment costs.

CCS Concepts: • **Hardware → Wireless integrated network sensors;** • **Social and professional topics** → *Remote medicine;* • **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**;

Additional Key Words and Phrases: RF sensing, Wi-Fi-based, camera based, software-defined radio based, radar based

ACM Reference Format:
Najah Abed Abu Ali, Mubashir Rehman, Shahid Mumtaz, Muhammad Bilal Khan, Mohammad Hayajneh, Farman Ullah, and Raza Ali Shah. 2024. Contactless Diseases Diagnoses Using Wireless Communication Sensing: Methods and Challenges Survey. *ACM Comput. Surv.* 56, 9, Article 226 (April 2024), 29 pages. https://doi.org/10.1145/3648352

1 INTRODUCTION

The process of exchanging air for gas is the respiratory system's primary function. The bloodstream absorbs oxygen (O_2) from the surrounding air, whereas carbon dioxide (CO_2) is exhaled into the atmosphere [1]. The respiratory rate, also known as breaths per minute (bpm), is a clinical parameter representing ventilation, or airflow, into and out of the lungs. As the body attempts to maintain O_2 delivery to the tissues, a change in respiratory rate is frequently considered the first sign of respiratory illness [2, 3]. Respiratory illness can occur when the rate or pattern of respiration is abnormal. The standard respiratory rate differs from person to person, but it lies within the range of 12 to 20 bpm when the person is resting [4]. Respiratory illnesses can cause slow or fast breaths per minute. These illnesses include tachypnea, bradypnea, Biot, sighing, Kussmaul, sleep apnea, and Cheyne-Stokes [5]. Bradypnea is characterized by slow and shallow breathing having a consistent pattern, whereas tachypnea has a rapid respiratory rate. Biot illness is characterized by deep breaths with periodic episodes of apneas, whereas Kussmaul is characterized by deep and fast breathing, usually seen in diabetic ketoacidosis. Sighing is a normal respiratory process punctuated with deep sighs. In addition, Cheyne-Stokes is defined by a gradual decrease and increase in respiratory rate. In contrast, sleep apnea is characterized by respiration that repeatedly stops and starts during sleep and is frequently classified as central if caused by deficiencies in respiratory system development or obstructive if caused by airway obstruction [6].

Providing continuous and long-term care to at-risk patients has been a motivating factor in developing state-of-the-art technologies. Patients would have more freedom and comfort if medical professionals could safely monitor vital signs without examining a patient in a hospital environment [7, 8]. Vital signs include heart/respiration rate, temperature, and blood pressure. Intelligent long-term care at home could reduce the burden on the healthcare system and the likelihood of readmission [9]. The contact methods require physical contact with the subject's body. Conversely, contactless monitoring techniques measure the subject's respiratory illnesses without physical contact with the subject's body. Depending on the sensor employed or the respiratory parameter intended to be measured, the contact and the contactless methods have their unique **Region of Interest (ROI)**. Contact-based methods have been presented in the literature [10–12]. Similarly, other works [13–16] have investigated methods that do not require physical contact. However, the authors skipped the descriptions of contactless techniques using wireless communication,

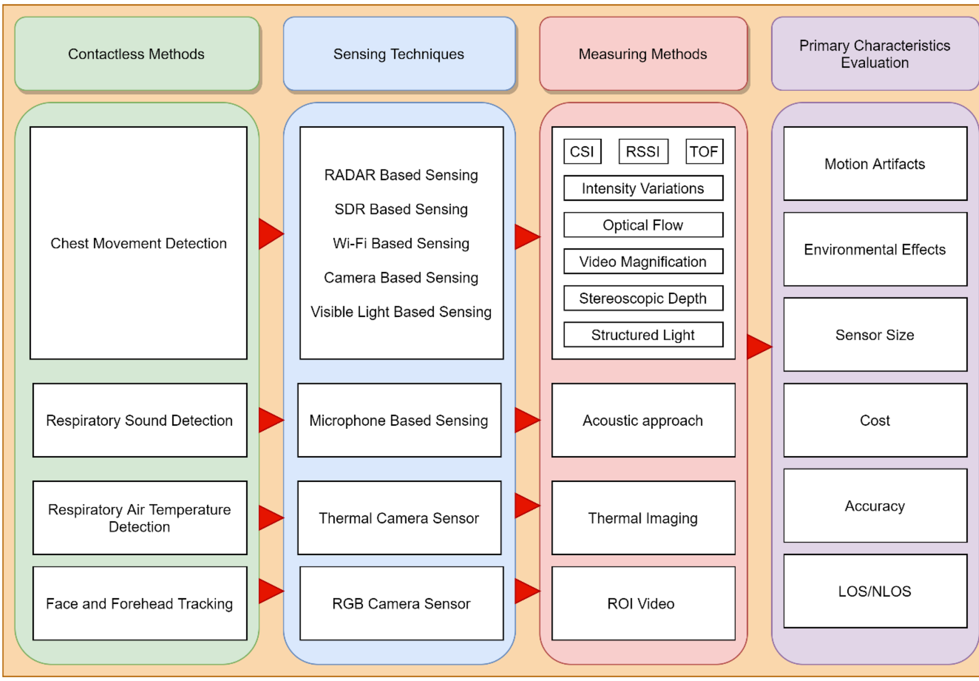

Fig. 1. Summary of contactless methods for diagnosis of respiratory illnesses.

such as **Radio Frequency (RF)** sensors, camera-based methods, and **Software-Defined Radio (SDR)**. This would be possible if reliable wireless communication sensing based healthcare monitoring devices were available in the market. The contactless methods for detecting respiratory illnesses are shown in Figure 1. This survey article aims to provide a comprehensive overview of the contactless methods using wireless communication sensing currently available for diagnosis and continuous monitoring of respiratory illness. This review work is broadly divided into four contactless methods: chest movement sensing, respiratory air sensing, respiratory sound sensing, and face/forehead sensing. Most of these methods are further split into subclasses, providing a comprehensive overview of the field. Each technique's working principle and primary characteristics are presented (cost, susceptibility, real-time monitoring of the human body, motion artifacts, etc.). Furthermore, the application of each method is also provided to anticipate the potential development and applicability of each method.

The rest of the survey is organized as follows. Section 2 covers the significant applications for diagnosis and continuous monitoring of respiratory illness. Section 3 discusses all existing contactless methods and technologies using wireless communication sensing for diagnosing and monitoring respiratory illness. Finally, conclusions from this survey are drawn in Section 4.

2 APPLICATIONS FOR DIAGNOSING RESPIRATORY ILLNESS

This section covers significant applications for the diagnosis of respiratory illness. The objective is to educate people about monitoring respiration's critical importance. Respiration has long been overlooked in the clinical setting and other fields, despite substantial evidence indicating that this vital sign responds to various stressors. The following application fields in which respiratory illnesses can be fully applied.

2.1 Occupational Settings

Increasing industrial development demands monitoring workers' activities to improve their health, well-being, and safety. For example, numerous wearable devices for assessing respiratory illness have been proposed to monitor workers experiencing high psychophysiological stress in the working environment [17, 18]. The continuous monitoring of respiration during work activities is essential due to the sensitivity of respiration to emotional stress, mental workload pain, environmental risks, and discomfort [19]. Remarkably, respiration has been suggested as a sensitive indicator of mental workload, with crucial implications for workers subjected to high-demand tasks, such as surgeons, soldiers, and pilots [20, 21]. Moreover, because it is strongly affected by body temperature, respiration can be seen as a marker of thermal stress [22]. It is essential in hot environments for workers and those carrying protective clothing that may inhibit thermoregulation, like firefighters [23].

2.2 Clinical Settings

Numerous pieces of evidence indicate that respiration is a highly useful vital sign. It is a predictor of potentially severe adverse events and a clear early indication of physiological decline [24, 25]. Respiratory illness is one of the indicators of cardiac arrest. Doctors recommend intensive care unit admission and a significant predictor marker for risk evaluation following a myocardial injury [26, 27]. In addition, it is essential to sense the threat of unhealthy conditions, including sleep apnea [28], respiratory stress in postoperative patients, and perinatal death [29]. Moreover, respiratory parameters are sensitive to numerous pathological conditions, including toxicology issues, diabetic ketoacidosis, dehydration, shock, sepsis, severe pain, and allergic reactions [30]. Nonetheless, respiratory illness diagnosis is underappreciated and under-recorded. Regardless of whether respiration is one of the four vital signs, it is measured clinically instead of objectively [26].

3 CONTACTLESS METHODS AND TECHNOLOGIES

Contactless measurement of respiratory illness is possible using a variety of methods such as chest movement detection, respiratory sound detection, respiratory air temperature detection, and face and forehead tracking.

3.1 Chest Movement Detection

During respiration, the diaphragm expands and contracts while intercostal muscles move the ribcage. Due to this, the chest cavity swells. Expiration relaxes the diaphragm and intercostal muscles, restoring chest volume. These movements cause 7-cm circumference variations of the chest wall [31]. Respiratory movements of the chest can be used to obtain respiratory parameters. Five sensor-based communication sensing technologies used for diagnosis of respiratory illness using chest movements detection method in include those that are radar based, SDR based, Wi-Fi based, camera based, and visible light sensor based.

3.1.1 Radar Based. Radar operates on a simple principle where it transmits bursts of pulses, reflects them off a target, and receives them as echoes. The signal $x(t)$ indicates a change in chest displacement, as depicted in Figure 2. Radar makes use of an echo principle. Different types of radar technologies are used in the literature, including **Ultra-Wideband (UWB)** radar, **Continuous-Wave (CW)** radar, **Frequency-Modulated Continuous-Wave (FMCW)** radar, ultrasonic radar, laser radar, and microwave radar. The performance summary of radar-based wireless communication sensing methods is provided in Table 1.

UWB Radar. UWB radar operates by sending periodic short pulses. The short pulses are reflected back with an extensive large bandwidth and provide several benefits, including high throughput,

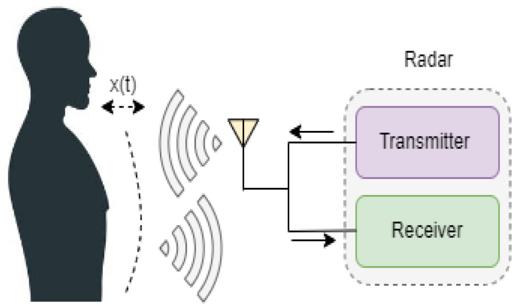

Fig. 2. Radar-based chest movement sensing.

Table 1. Summary of Radar-Based Sensing Methods

Technology	Motion artifacts	Environmental effects	Sensor size	Cost	Accuracy	LOS/NLOS
UWB radar	Medium	Medium	Large	High	Medium	NLOS
CW radar	Medium	Medium	Large	High	Medium	NLOS
FMCW radar	Low	High	Large	Medium	High	NLOS
Ultrasonic radar	High	High	Large	High	Low	NLOS
Laser radar	High	High	Large	Low	Low	LOS
Microwave radar	High	High	Large	Medium	Medium	NLOS

lower power resistance to jamming, and coexistence with radio services [32]. UWB radar not only can transmit a large amount of information with very little power over a short distance but also can move through objects that reflect narrow-bandwidth signals. However, due to expensive hardware, UWB radar applications are typically restricted [33]. Except for Wi-Fi at 5 GHz, the UWB radar frequency range (3.1–10.6 GHz) is interference free. UWB radar systems have low complexity, lower power consumption, noise resistance, and good integration with narrowband links [34]. Due to its low radiated power, it has no adverse impacts on the human body. The UWB link's limited coverage is its primary drawback. However, UWB pulsed radars that transmit narrow pulses with a broad instantaneous bandwidth have been developed. Yet, narrowband receiver architectures can be utilized with this wide bandwidth. The correlation receiver is one of the optimal solutions [35–38], which uses a pulse generator to generate short pulses that are then transmitted to the target. Unlike CW radars, UWB radars require no frequency conversions, resulting in less computational complexity and reduced power consumption. The phase and time delay between echo and transmitted pulse can be processed to assess respiratory illnesses. Unfortunately, the system only encodes phase information and cannot discriminate between different respiratory rates. Furthermore, higher frequency exposure is a problem for infants. Ferrigno et al. [39] reported on a UWB radar system to extract respiratory parameters using a peak detection algorithm. The study's findings are consistent with commercial ECG-based sensors.

CW Radar. CW radars have a less complex structure than UWB radars. A known stable frequency of CW radio energy is transmitted, and an echo is received after reflection from objects. Unlike UWB radar, CW radar cannot measure the delay time, making distance estimation difficult. Furthermore, the transmitter and receiver are coupled in a CW radar, generating low-frequency noise and direct current bias. This strongly affects respiratory illness estimation results. Folke et al. [40] and Grassmann et al. [41] demonstrated the use of CW radar for recording the respiratory illness of elderly patients suffering from pneumonia.

FMCW Radar. FMCW radar has been used in previous studies to detect respiratory illnesses and obtain promising results. The transmitted radar signals show frequency variations, which helps find the distance between the FMCW radar sensor and the patient [42]. The amplitude variations in the reflected signals change when the patient breathes, which helps measure the distance between the transceiver device and the chest wall. FMCW radar necessitates a large frequency bandwidth because chest movements can be subtle, even on a scale of millimeters [43, 44]. Hassan et al. [45] implement a 24-GHz FMCW radar system for measuring the vital signs of multiple people in the same environment. Grassman et al. [42] developed an FMCW radar system for real-time detection of respiratory illness on multiple actual patients in the clinical scenario. FMCW radar performed well when compared to a reference instrument (capnography). FMCW radar radiates signals after linear frequency modulation covering a broad frequency bandwidth [46]. Helfenbein et al. [47] use FMCW radar to extract reflected signals from multiple persons depending on propagation time. However, this system fails when multiple persons are present nearby. Holt et al. [48] demonstrated that this problem can be solved using an independent component analysis method.

Ultrasonic Radar. Contactless monitoring of respiratory illnesses can be accomplished using ultrasound waves. The working principle is that an ultrasound transmitter is exploited for radiating ultrasound waves toward the patient or subject, and the reflected waves are used to measure respiratory illnesses. As demonstrated in some works [49–52], an ultrasonic radar can be used to measure respiratory illnesses. The space between the subject and the radar sensor is calculated using the sensor's attenuation characteristics. Janssen et al. [51] used phase detection to differentiate movement artifacts due to non-respiratory activities. This developed system employs a phase-canceling technique to extract the subject's respiratory motions allowing for the detection of large body activities while retaining respiration signals. The prototype was designed to sense chest motions and from which respiratory parameters can be measured.

Laser Radar. Laser radar is a contactless optical technique that utilizes the Doppler shift for measuring displacement and surface velocity. Laser radar, as opposed to RF radar, is used to obtain the shift in laser frequency. This frequency shift, in turn, helps monitor chest movement by providing additional information. Laser radar is a technique that detects the Doppler shift in scattered light by directing a laser beam at a moving chest wall surface, which is caused by respiratory activity [53]. This shift can be seen when the laser beam is scattered. This method exploited chest wall movements for estimating respiratory information [54–57]. Kempfle and van Laerhoven [56] implemented laser radar based contactless respiratory illness sensing, and the system was installed at a distance of a few meters from the subject. Similarly, Khan et al. [57] proposed a system for monitoring the respiratory activity of infants. Laser radar based systems have high sensitivity and require low power density, implying no harmful effects on humans. However, the equipment is costly. The high cost of equipment and the substantial influence of motion artifacts on results have been emphasized in a recent review of laser radar applications in clinical and occupational settings [58–60]. Several authors investigated this technique for real-time respiratory illness sensing of infants and the elderly. Respiratory and heartbeat signals can be concurrently extracted from abdominal or chest movements, facilitated by the high sensitivity of laser radars [61, 62]. This sensitivity was demonstrated in the extraction of respiratory parameters for multiple healthy subjects in a resting position. The main limitation of using laser radar sensing is the back-reflected signal's reliance on the nature of the surface. The problem is usually solved by applying a reflective layer or a small amount of oil drops on the chest wall [63]. In addition, a laser radar sensor can only measure the signal at a single point of focus, which is usually strongly affected by non-respiratory physical movements. Consequently, this method cannot be exploited to monitor respiration during athletic activity. As well, this method is discouraged for real-time respiration monitoring in domestic and clinical settings.

Microwave Radar. A vital sign monitoring system that does not require direct patient contact was discussed in the work of Levai et al. [64]. The microwave radar sensor system was developed to restrict the patient's contact with toxic environments in the event of a biochemical hazard. The system includes a 10-GHz respiratory radar and a 24-GHz cardiac radar. The isolator (10 GHz) gathers chest wall modulated reflected microwaves, whereas the 24-GHz radar monitors cardiac motions. The simultaneous extraction of respiratory and heart values can be accomplished with the help of microwave radar.

Summary. The transmitted signal is sent in a radar system, and the range can be obtained by measuring the returned signal's frequency [65]. The respiratory-induced ribcage movement modulates the returned signal. This permits the measuring of respiratory illness detection based on chest movement. CW and FMCW Doppler radar transmit a signal with a uniform frequency and amplitude and process the reflected echo signal from a moving target [66]. The design of CW radar is a relatively simple process.

Nevertheless, multipath reflections and environmental noise significantly hinder performance [32]. Compared to CW Doppler radar, FMCW radar's bandwidth of 1 to 2 GHz makes it possible to avoid noise and interference effects [67]. However, wide bandwidth requires precise peak signal strength and pulse width [68]. Due to the extreme sensitivity of laser radar, it is possible to obtain the heart and respiratory signals simultaneously. However, like ultrasonic radar recording, laser radar recording is prone to be heavily impacted by motion artifacts. In addition, laser radar needs to be directed at a particular measurement point to obtain high-quality recordings of the received signals.

3.1.2 SDR-Based Sensing. Diverse SDR sensor-based systems for respiratory illness diagnosis and continuous monitoring have been explored in the literature. Loo et al. [69] propose contactless sensing using an SDR-based system for accurate measurement of breathing rate and heart rate based on minute movement of the chest. The system used directional antennas and RF component analysis by a vector network analyzer (VNA). Additionally, the proposed system is investigated by changing the distance between the subject and the directional antennas. Moreover, experiments through wall monitoring are conducted, and performance is evaluated. In the work of Lovett et al. [70], a multi-frequency band CW radar system is implemented using the SDR-based sensor to diagnose and monitor breathing at pre-determined distances. In the work of Lucas and Kanade [71], the channel response is analyzed in the frequency domain to identify small-scale variations in multi-carrier orthogonal frequency division multiplexing (OFDM) subcarriers due to the human body's movements over wireless communication channels. As depicted in Figure 3, the developed SDR-based platform accurately detected and identified waving hand movement, abnormal coughing, and numerous respiratory illnesses. In the work of Luck [72], a contactless respiratory illness sensing system is developed using SDR sensing. This platform used **Channel State Information (CSI)** to record the time history of minute movements caused by breathing and diagnose three distinct breathing abnormalities. In the work of Lv et al. [73], the design of a system is evaluated by first investigating the coefficient of channel frequency response (CFR) for three simulated channels. Machine learning algorithms were used in research to classify respiratory illnesses successfully. In the work of Marcel-Millet et al. [74], SDR-based breathing pattern sensing detects and classifies six abnormal breathing patterns. That work is further extended by Lucas and Kanade [71] by classifying up to eight breathing patterns. SDR-based sensing in healthcare holds promising

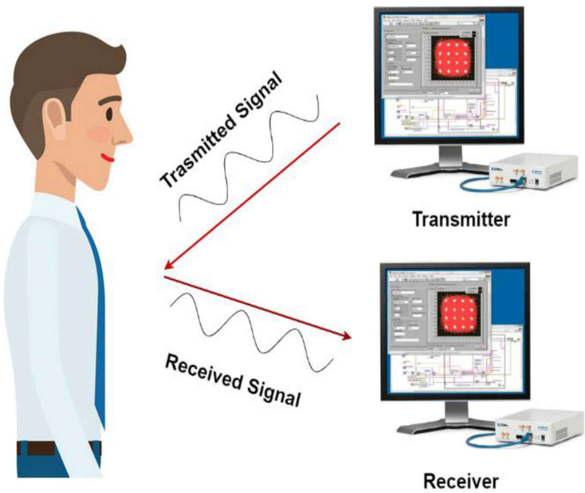

Fig. 3. SDR-based chest movement sensing.

Table 2. Summary of SDR-Based Sensing Technology

Motion artifacts	Medium
Environmental effects	Medium
Sensor size	Medium
Cost	Medium
Accuracy	High
LOS/NLOS	Both

developments. The Internet of Medical Things (IoMT) is expected to expand, allowing for interconnected networks that communicate through SDR-based sensing. Telemedicine will take advantage of reliable wireless communication between patients and healthcare providers. The generated health data can be integrated with artificial intelligence developed models to extract meaningful insights from large datasets. This can lead to better predictive analytics, early disease detection, and personalized treatments. As 5G networks become more widespread, SDR-based devices can leverage high-speed and low-latency communication, enhancing real-time remote diagnostics and healthcare services. SDR-based sensing can lead to improvements in non-invasive imaging techniques, such as using wireless signals for imaging and monitoring internal body structures. With advancements in SDR technology, there is potential for doctors to perform remote monitoring using tactile feedback and real-time imaging. SDR-enabled devices can support bridging the healthcare access gap in remote or rural areas, where traditional infrastructure is lacking. SDR-based sensing has the potential to revolutionize healthcare applications by enabling flexible, portable, adaptable, and remote sensing capabilities. Its future implications could lead to more advanced and accessible healthcare services, improved diagnostics, and personalized treatments. A summary of SDR-based sensing technology is provided in Table 2.

3.1.3 Wi-Fi-Based Sensing. Contactless Wi-Fi-based sensing for respiratory illness diagnosis and monitoring has grown in popularity in recent years. Due to the widespread implementation

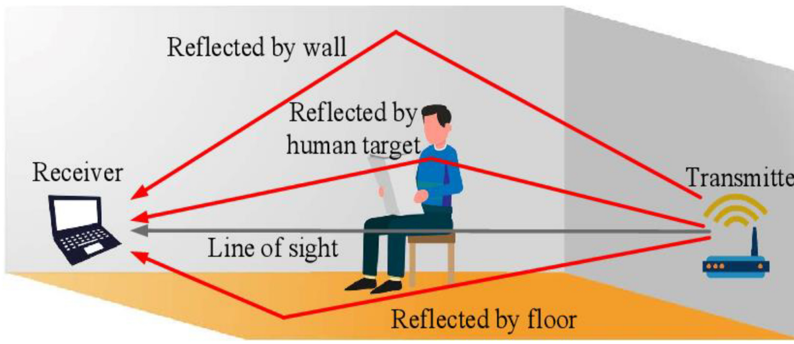

Fig. 4. Wi-Fi-based sensing using the chest movement method.

Table 3. Summary of Wi-Fi-Based Sensing Methods

Approach	CSI based	RSS based
Motion artifacts	Medium	High
Environmental effects	Medium	High
Sensor size	Medium	Medium
Cost	Low	Low
Accuracy	High	Medium
LOS/NLOS	NLOS	NLOS

of readily available wireless devices, Wi-Fi-based sensing has received increased attention. Wi-Fi waveforms are generally gathered from the Wi-Fi devices using application program interface software. Wi-Fi sensing techniques, as shown in Figure 4, typically use two approaches: CSI and **Radio Signal Strength (RSS)**. A summary of Wi-Fi-based sensing is provided in Table 3.

CSI Based. Specific indicators in CSI include carrier signal strength, amplitude, phase, and signal delay. Because of its high-dimension structure, CSI contains useful information and supports fine-grained respiratory data for classification applications [75]. CSI has emerged as a viable option for improving Wi-Fi-based sensing accuracy. Each entry of the CSI matrix represents the phase and amplitude information of the wireless channel. Consequently, the CSI's amplitude information represents signal dissipation due to the multipath fading. RSS-based sensing is only helpful when the Wi-Fi access points and subject are in the **Line of Sight (LOS)** and close to each other. However, CSI-based approaches can extract respiratory information even from a distance. In general, CSI-based sensing can be explored by two methods: CSI phase based and CSI amplitude based.

The *CSI phase-based method* extracts the phase information from the wireless channel. A contactless approach for diagnosing and monitoring respiratory illnesses utilized a CSI phase-based method [76]. The phase distortion and low-frequency noise are eliminated using a Hampel and high pass filter. Massaroni et al. [77] presented a model design for sleep study monitoring that uses ambient radio signals to identify sleep stages and examine sleep quality, including respiration rates. The authors used a statistical analysis approach to investigate the autocorrelation of the CSI-based response, which significantly decreases the time delay and yields quick estimation. Due to insufficient spatial resolution, CSI phase-based methods evaluate only one person in the observation area. The extended CSI phase-based method [78] uses the phase difference between antennas to eliminate phase distortions introduced in the internal circuit of the system. The minor displacement produced by respiration affects the CSI phase-based measurement on all antennas. The phase difference between antennas is the subtraction of two periodic signals rather than the actual respiratory movement.

The *CSI amplitude-based methods* are used for extracting respiration signals by exploiting Wi-Fi devices. In 2017, Massaroni et al. [79] introduced a contactless respiratory illness sensing platform system by applying the time-reversal technique on CSI acquired from Wi-Fi devices. The authors captured the small-scale periodic variations in CSI patterns caused by respiration activity. In another work, Massaroni et al. [80] applied the Root-Music algorithm to attain highly accurate respiratory parameter extraction. In a later work [81], high-frequency noises and outliers are removed by using Hampel and wavelet filters on the CSI time series data. Then, respiratory rates are measured by applying FFT on all CSI amplitude-based data. Finally, this technique helps to solve the multi-person respiration rate measurement problem in the same environment. Massaroni et al. [82] also proposed a continuous respiratory illness system for multiple persons using the CSI amplitude-based method with a pair of Wi-Fi devices. The authors eliminated the limitation of a single person in the area of interest. Later, the authors also demonstrated a calibration-free respiratory illness diagnosis system for multiple persons using Wi-Fi access points. However, the CSI amplitude-based spectrum sensing methods require a significant delay to achieve better frequency resolution, and they cannot detect sudden variations in respiratory rate. In 2018, Massaroni et al. [83] proposed one of the first respiratory monitoring systems for measuring respiratory information for a single person in the environment. The results were improved in another work [84] by extracting respiratory information during sleep. These systems are based on the idea that CSI amplitude exhibits a sinusoidal-like pattern in the time domain due to a person's respiration movement. Mei and Ling [85] elaborated on the blind spot problem by applying the Fresnel zone theory in single-person respiration sensing. Min et al. [86] show the amplitude information for respiration detection to eliminate blind spots. Min et al. [86] and Mohammed et al. [87] proposed solutions to the blind spot problem. Unfortunately, the proposed methodology cannot be applied directly to a multiple-person scenario, as the theoretical basis for eliminating blind spots emphasizes that only one living person is breathing.

Based on the analysis, two persons' respiration frequency can still be well preserved if the CSI amplitude is converted to the frequency domain. Moll and Wright [85] and Mei and Ling [85] highlighted that the proposed system performance can be highly affected due to the blind spots problem. Moll and Wright [88] and Mutlu et al. [89] demonstrated that the CSI phase difference between two antennas can be used to estimate multi-person respiratory rates using the Root-Music algorithm. Nakajima et al. [90] utilize tensor decomposition to retrieve respiration information from CSI phase difference, supposing that the difference is the sum of sinusoidal respiration patterns [79]. Initially, Wi-Fi-based CSI is projected into the time-reversal resonant strength feature space before the Root-Music algorithm is utilized to assess the breathing rates of numerous targets. These methods presume that the respiration rates of different individuals are unique, and their performance accuracy declines when these respiration rates are in close range. Massaroni et al. [81] monitored the breathing of various persons by optimizing the placement of Wi-Fi transceivers so that a single target only influenced the transmission of each transceiver pair. However, this strategy needs to know each individual's location in advance; if one individual's location changes, the system may fail.

RSS Based. The RSS-based sensing approach offers coarse-grained information about communication channels and can be easily measured using wireless devices [91]. The RSS-based approach is a measurement of the received radio signal power at the receiver. RSS-based techniques have applications in different fields, including driving behavior [92], crowd counting [93], and hand gesture recognition [94]. However, RSS can easily be corrupted by channel parameters such as the

Table 4. Summary of Camera-Based Sensing Methods

Technology	Motion artifacts	Environmental effects	Sensor size	Cost	Accuracy	LOS/NLOS
RGB camera	High	High	Low	Low	Medium	LOS
Depth camera	High	Low	Low	High	Medium	LOS
Body marker based	Low	Low	Medium	Medium	Medium	LOS

multipath effect and channel noise. The RSS-based approach is only used for LOS transmission, resulting in indoor respiration detection, and limiting the application services [75, 95]. The use of RSS-based measurements method identifies the person's respiration rate to diagnose respiratory illnesses in a home environment. This method addresses the challenge of subject movement during respiratory activity. They have presented a method used in their previous work [96] to estimate respiratory illnesses. This technique computes the power spectral density for each channel using the most recent data, averages the power spectral density across all channels, and calculates respiratory information.

The key challenge was that the channel that effectively measured chest movement was also the channel that effectively measured other body movements. The RSS-based approach has high susceptibility noise that makes it inappropriate for assessing respiratory parameters, although it identifies minor human body movements. The respiration measurement used RF transceivers to extract respiratory rates, which was enhanced by Poh et al. [97], where the RSS-based method from a single antenna pair can measure respiratory rates. Comparatively, the RSS-based approach is not a sensitive indicator for accurate measurement of minute movement of the chest. As a result, environmental noise can affect the exhaling and inhaling phenomena causing minimal changes in RSS. Praktika and Pramudita [98] proposed a comprehensive examination system for extracting respiratory signals from noisy Wi-Fi-based RSS. Several challenges were addressed, including channel noise reduction, interference with other humans, unexpected user body movements, and detection of various respiratory parameters.

Summary. Wi-Fi-based sensing has received substantial attention in the field of respiratory illness sensing. CSI and RSS are two ways of acquiring respiration information from the channel. CSI is a signal characterization index that gives a more satisfactory resolution than RSS, offering fine-grained information. In addition, by examining the properties of multi-channel subcarriers, CSI can prevent the impacts of multipath and noise. Unlike CSI, which is easily distorted by the multipath effect, modern RSS methods usually need LOS transmission.

3.1.4 Camera Based. Camera-based technology is used for detecting respiratory illnesses in a contactless manner. Many different camera technologies can be utilized, including RGB cameras, depth cameras, and marker-based motion-sensing cameras. A summary of camera-based sensing methods is provided in Table 4.

RGB Camera Sensor. Cameras with RGB (red, green, and blue) channels have been tested in recent years to extract respiratory illness data from chest movements [99–105]. Furthermore, all of these devices operate with visible-spectrum signals. As shown in Figure 5, RGB cameras integrated into webcams can record video frames at a high enough sample to allow for the extraction of data regarding respiratory illnesses. Three different methods can be utilized for the sensing of RGB cameras: analyzing the intensity variations of pixels [106–108], computing the optical flow signal [109–112], and video magnification [113].

Intensity variations measurement can determine respiratory parameters by detecting chest movement associated with respiration. Procházka et al. [99] described a method for detecting ROI in

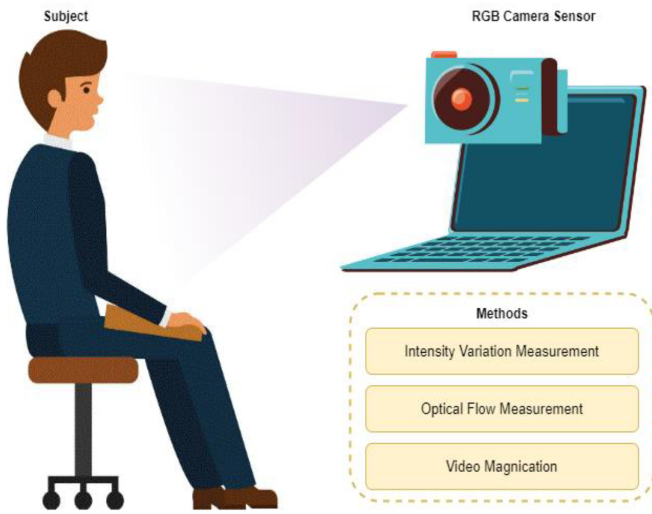

Fig. 5. RGB camera based chest movement sensing.

the neck pit and analyzing changes in intensity. Compared to an airflow sensor as a reference, this method estimates the respiration parameters by post-processing video frames [99]. Respiratory illness is measured through intensity variation in videos recorded by a smartphone camera [114, 115], and a portable and low-cost respiratory smartphone-based system is demonstrated.

Extracting information about respiration could be accomplished by analyzing the *optical flow* of surface human body motions due to respiration [116]. Using two RGB cameras, two fiber grating sensors, and two 3D vision sensors, Schmidt [117] obtained the respiratory parameters. Sanyal and Nundy [109] used the optical flow method to extract respiratory information by extracting optical flow at every pixel along the image gradient. This provides a computationally efficient solution. Once tested on healthy volunteers, the results were promising compared to impedance pneumography values [109]. Shan et al. [118] investigated the performance of the Kanade-Lucas algorithm in detecting optical flow derived from respiratory activity.

Sirevaag et al. [119] demonstrated *video magnification* of chest movement to detect respiratory parameters. Using video imaging, the researchers extracted the timing parameters of a sleeping respiratory cycle. However, the respiratory movements were impossible to observe with the naked eye. Hence, video magnification was performed using an elliptic filter and wavelet decomposition. Despite the body's movements, the technique successfully measured the respiratory parameters. Yet, the method yielded no real-time measurements. Scalise et al. [113] magnified tiny respiratory movements by applying post-processing techniques. Furthermore, Smith et al. [120] applied the Hermite magnification technique to estimate respiratory illness in healthy subjects in various positions.

Summary. The use of RGB cameras is currently confined to structured and static environments. The most significant shortcoming of these sensors is their susceptibility to motions not associated with respiration, which severely limits the technique's applicability in a broader range of applications, including sports activities. Furthermore, environmental light changes must be avoided during data collection to ensure accurate respiratory data collection. Moreover, this approach cannot be used at night without a continuous light source. Camera-based sensing systems encounter occlusion issues, such as tracking individuals in crowded environments or monitoring moving

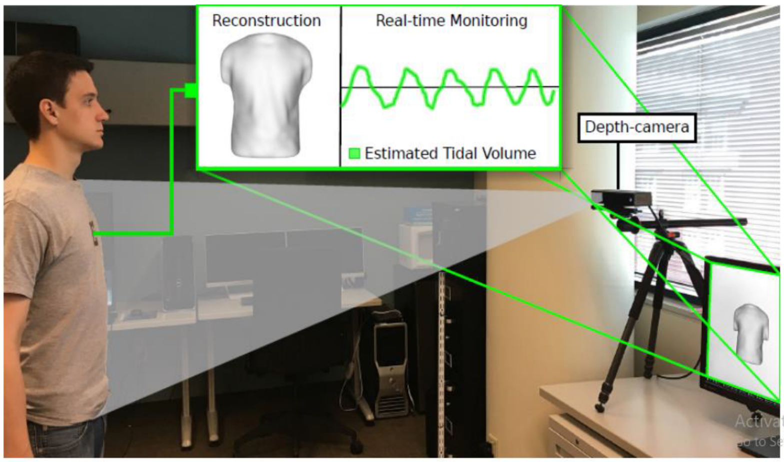

Fig. 6. Depth camera based chest movement sensing. Adapted from Smith et al. [121].

objects behind obstacles. Lighting variations can affect the performance of camera-based techniques in industrial settings. Adaptive exposure control algorithms, dynamic range expansion, or the use of additional lighting sources can address these challenges. Optimal camera positioning plays a critical role, involving the placement of cameras to ensure optimal perception, accounting for factors like blind spots, field of view, and perspective distortion. The application of camera-based techniques in medical imaging, with its stringent image processing demands, is an area of exploration. Real-time imaging proves essential, particularly in procedures like minimally invasive surgeries or endoscopy. Employing real-time image enhancement algorithms, such as noise reduction techniques and efficient compression methods, facilitates precise visualization and diagnosis.

Depth Camera Sensor. Depth camera sensors can obtain depth information by reconstructing the chest wall surface [121], as shown in Figure 6. In the literature, three approaches for depth camera sensors are used: stereoscopic depth cameras, structured light based depth cameras, and **Time of Flight (ToF)**-based depth cameras.

Stereoscopic depth camera sensors, also known as RGB depth cameras, estimate depth by observing a distant target while it is illuminated from various angles by a projector. Stereoscopic depth cameras find depth by viewing the same scene from two slightly different perspectives. This is how frontal-vision animals see depth. Depth is calculated from two viewpoints by comparing image features.

A pattern is projected onto a scene by *structured light based depth cameras.* Patterns, such as stripes, are identified, and depth is determined by examining distortion in the scene. The sensors of structured light cameras are composed of one camera and capture the pattern formed by a projector on the subject. Therefore, these cameras are referred to as single-camera structured light cameras. This approach requires a projected laser source or light pattern and a camera detector. The light source displays a structured pattern for camera triangulation. In the work of Soleimani et al. [122], Kinect V1 (a structured light sensor) extracted respiratory data from camera depth information. Furthermore, an ROI detection algorithm was demonstrated for automatic chest depth measurement. The respiratory information obtained from a Kinect depth sensor was in good agreement when compared with the spirometer, as in another work by Soleimani et al. [123]. Stove [124] used electrocardiographic impedance pneumography as a point of reference while collecting respiratory data from infants.

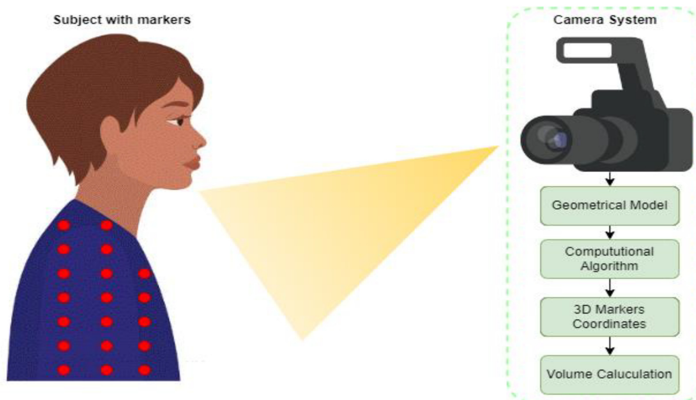

Fig. 7. Marker-based chest movement sensing. Figure adapted from Wang et al. [135].

ToF-based depth cameras measure the time required by a signal to return after reflection from the subject. This demands continuous illumination of the scene by the emitter's camera, which is usually an infrared laser. The light detection and ranging principle is the core component of the operation of depth camera sensors based on ToF [122]. This particular kind of depth sensor has seen extensive use for monitoring data related to respiration [123–130]. There are widespread ToF sensors as well, such as the Microsoft Kinect v2. A light emitter and a light detector comprise the foundation of a ToF system. The emitter sends a modulated signal reflected by scene objects and detected by the receiver upon its return. The round trip time between the transmitter and receiver indicates the object's distance from which the signal was reflected [131]. Van Gastel et al. [132] proposed a remote contactless approach to respiratory illness sensing in clinical settings using a Microsoft Kinect V2 to re-create the chest wall capacity. This work was expanded by Vanegas et al. [133], highlighting the advantages of using two ToF systems instead of a single Kinect. Furthermore, the experimental tests demonstrated the method's robustness when different types of clothing were worn. Viola and Jones [134] presented a demonstration of a respiratory information system for infants, during which they found that the ToF-based depth system and a Piezo belt reference system had an excellent level of agreement with one another.

Summary. Whenever a patient's skin is not exposed, or the ROI is hard to trace or identify, depth sensors could be chosen over an alternative approach. Furthermore, unlike other optical sensor based approaches, changes in environmental illumination do not affect distance sensors. However, movements unrelated to respiration that can occur during data extraction significantly impact accuracy.

Body Marker Based Motion Sensing Camera. During respiration, the chest wall rises and the interior volume increases. To capture these motions, photo-reflective markers can be placed on the subject's chest, as shown in Figure 7, and their movements are monitored by specialized cameras and software [135, 136]. Despite the placement of markers on the subject, this technique is deemed contactless since the camera does not make a physical connection with the subject. Marker-based systems operate by detecting markers to determine 2D or 3D motions. At least two cameras are required to apply the triangulation principle. Triangulation methods permit the estimation of the 3D coordinates of a marker by analyzing the target from multiple angles. Technically, two markers captured by a single camera are sufficient to estimate the respiratory parameters when the person rests [137]. Additional markers and cameras are required to replicate the chest cavity and retrieve

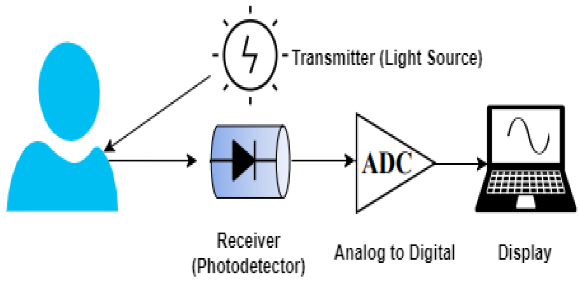

Fig. 8. Visible light sensor based chest movement sensing. Figure adapted from Yang et al. [146].

Table 5. Summary of the Visible Light Sensor Based Sensing Method

Motion artifacts	High
Environmental effects	High
Sensor size	Low
Cost	Low
Accuracy	Low
LOS/NLOS	LOS

usable respiratory data when body movements are unassociated with respiration, such as during sports. Wang et al. [138] were the first to employ marker-based systems for respiratory illness detection. At the same time, this work is expanded by using technological breakthroughs in video technologies and processing capacity [139]. In this study of Wei et al. [139], four cameras followed 32 photo-reflective markers placed on 32 bodily landmarks. This method is also recognized as optoelectronic plethysmography [140].

Summary. The main advantage of marker-based motion capture systems is the ability to extract respiratory parameters in various scenarios, mainly when motion artifacts are present due to unrelated respiratory movements. When other contact-based or contactless techniques fail, this technique may be effective. This is why marker-based systems are widely exploited in outdoor sports activities. These systems are also widely deployed in clinical settings, especially for newborns [141–145]. However, this sensing method has a few limitations, including the need for predetermined working space calibration, the high expense of specialized devices (including camera systems and markers), and the time and processing cost required to interpret the 3D trajectories. This technique is extensively used in studies to obtain respiratory data and monitor athletes. In conclusion, marker-based systems are not optimal for detecting respiratory disease in household and clinical environments.

3.1.5 Visible Light Sensor. Visible light sensors, such as photodetectors, can be used for respiratory illness sensing. Yang et al. [146] proposed a contactless respiratory system based on a visible light sensor and a data processing unit. Figure 8 presents a respiratory illness diagnosis system, and results with accuracy up to 5 bpm are observed. Various postures of subjects are considered during the experimentation with a day and night scenario. A summary of the visible light detector based sensing method is provided in Table 5.

Summary. Visible light sensors are still used, but only in extremely controlled environments and for monitoring resting subjects. The key restriction is the susceptibility of these sensors to motions unrelated to respiration, which severely restricts the technique's applicability to a wide

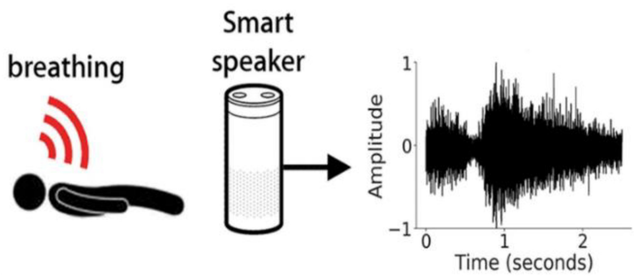

Fig. 9. Microphone sensor based respiratory sound sensing. Figure adapted from Yue et al. [151].

variety of fields. Changes in illumination must be avoided during data collection to ensure proper data recording and extraction of respiratory parameters. Furthermore, this approach cannot be used at night since no continuous illumination sources are available.

3.2 Respiratory Sound Detection

The respiratory sound detection method uses a microphone sensor to diagnose respiratory illness. The changes in air pressure caused by sound waves can be converted into an electrical signal using a transducer such as a microphone. Transducers are devices that allow for the conversion of one physical quantity into another. A contactless recording of respiratory sounds can be successfully carried out using home assistants and smartphones in various settings [147–150], as shown in Figure 9. Every microphone used in this environment must have a sampling rate greater than the usual sound frequency of human respiration. An acoustic approach to measuring respiratory parameters has recently gained popularity, particularly in home settings. A method for recording respiratory sound signals from the head using a microphone and extracting respiratory features from the sound was developed and implemented by Yang et al. [147]. Utilizing feature extraction and classification algorithms, the scientists identified inhaling and exhaling events, distinguished noise frequencies, and detected snoring occurrences in sleeping individuals. These algorithms were applied to filtered respiratory sounds with a frequency range of 0 Hz to 5 kHz. In contrast, Yu and Horng [148] used the smartphone microphone to approximate the volume and airflow of breath based on respiratory sounds. The user was a few feet away from the phone microphone when the study was conducted. Experiments conducted on healthy subjects in an environment with a low background noise level demonstrated good performance for respiratory illness sensing [149]. To record the patient's respiratory patterns, Yuan et al. [150] used a smartphone with a built-in microphone and placed it a few centimeters away from the subject's mouth. Lately, a home environment equipped with an Amazon Echo (an intelligent speaker) was exploited to differentiate between several respiratory illness patterns in a continuous real-time manner [151]. A support vector machine was used to distinguish between different respiratory illnesses based on the sounds of respiration that were recorded at a frequency of 8 kHz, with the provision that various respiratory illnesses have distinct frequency compositions. Zeng et al. [152] developed a smartphone application that analyzes acoustic samples taken from the user's Bluetooth to detect respiration using an innovative method based on accelerometer and microphone data.

The results of this study indicate that respiratory illness sensing values perform well in indoor settings. A summary of respiratory sound based sensing methods is provided in Table 6.

Summary. Compared to other techniques, acoustic approaches have certain advantages. Many people have access to commercially available technologies (e.g., smartphones and home assistants)

Table 6. Summary of Respiratory Sound Based Sensing Methods

Motion artifacts	High
Environmental effects	High
Sensor size	Low
Cost	Low
Accuracy	Low
LOS/NLOS	NLOS

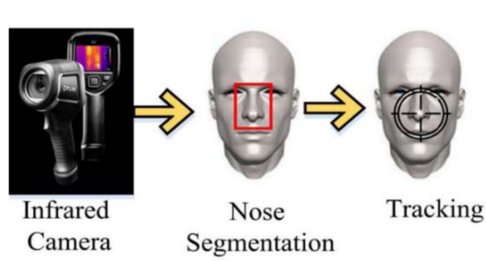

Fig. 10. Thermal camera based respiratory air temperature sensing. Figure adapted from Ali et al. [14].

that can extract respiratory parameters. However, no studies concentrate on continuously monitoring respiratory parameters using solutions tested against a standard system. Most studies provide technology solutions without validating them on clinical patients, limiting their relevance in the real world. Due to the inherent vulnerability of respiratory sounds to numerous environmental interferences, obtaining robust respiratory sounds in particular settings (e.g., traffic and gym) might be challenging. Moreover, other authors' methods use ML algorithms to process data, although they still cannot extract real-time respiratory parameters [153, 154]. The robustness of these approaches for real-time tracking of respiratory parameters requires further research.

3.3 Respiratory Air Temperature Detection

If an object's temperature is above zero Kelvin, it will emit radiation at a specified rate and with a wide range of wavelengths. The temperature of the object has a relationship that is proportional to the wavelength distribution. The creation of a contactless respiratory illness system could benefit from the utilization of thermal imaging cameras. Due to the fluctuating temperature surrounding the nose during respiration [155], respiratory air temperature can be used to diagnose respiratory illnesses.

The temperature of the exhaled air can be measured with a thermal or infrared camera, which can be used to diagnose respiratory illnesses. Thermal camera based respiration sensing [14], as shown in Figure 10, involves three steps: identifying the ROI (the nose), sensing it, and processing the data. ROI can be identified using segmentation [156–158], classification [159], or depth maps [160, 161] utilized a thermal camera with infrared sensors. Procházka, Aleš, et al. measured the variations in temperature around the neck and nasal region. To extract the parameters of respiration, a wavelet analysis method was devised. In a different study, Schleicher et al. [162] utilized a thermal camera to record respiratory data related to variations in skin surface temperature around the nose. The camera was positioned on a tripod 1 m away from the person. After recording and image segmentation, an algorithm was utilized to detect and track ROI around the nose. The selected ROI was subdivided into eight equal-sized concentric segments. The method was performed

Table 7. Summary of Respiratory Temperature Based Sensing Methods

Motion artifacts	High
Environmental effects	High
Sensor size	Low
Cost	Low
Accuracy	Low
LOS/NLOS	NLOS

for each image. The average temperature was plotted against time for each segment. These graphs depicted the respiratory signal linked with each segment. During inhalation, the respiratory signal's amplitude reduces, whereas during exhalation, it increases. Finally, an algorithm was created to extract respiratory characteristics from the recorded signal automatically.

Zhu et al. [157] and Zito et al. [159] used an algorithm, whereas in the work of Yang et al. [163], a camera equipped with an infrared sensor was installed on a tilting platform, to reduce the computational resources required for tracking and segmentation. After a signal has moved through a low-pass filter to eliminate noise, it is often subjected to processing. The most common techniques for processing the filtered signal are autocorrelation and curve fitting [164–166] describes an algorithm for extracting respiration signals from pixel time series that does not require nose-tracking or image segmentation. Lee et al. [167] extracted respiratory information from a thermal camera video and used a deep neural network to differentiate between different respiratory rates. Li et al. [168] described a clinical study that developed a thermal imaging technique that automatically tracks respiratory rate. The technology sensed and monitored variations in the nose tip's skin surface temperature. Thermal images were post-processed, filtered, and segmented to identify the nasal region accurately. In addition, Fang Zhao et al. developed a tracking and identification algorithm for the nose region. This technique attained respiration rate estimates highly associated with those acquired using traditional contact-based approaches. By detecting temperature variations induced by respiration, a thermal sensor can be employed to track a patient's respiratory rate [169]. Khanam et al. [170] coupled thermal camera based respiratory illness sensing with feature extraction to develop a robust contactless system. The drawback of this contactless sensing is that the positioning of thermal sensors must be close to the patient's head, whereby rotating the lead in a different direction may decrease the accuracy. In addition, feature selection is manual and needs individual calibration. The summary of the respiratory temperature based sensing method is provided in Table 7.

Summary. Fields of sleep disorder research and medical robotics could benefit substantially from thermal camera based respiratory illness sensing. However, it is computationally costly due to the time it takes for each subject's images to be processed. Furthermore, tracking inaccuracies for moving subjects make it susceptible to error [50]. This method can extract the respiratory rate during head motion, but if the mouth is not segmented, breathing through both the mouth and the nose can be a source of error.

3.4 Face and Forehead Tracking

The face and forehead tracking method used RGB cameras for diagnosing respiratory illness as shown in Figure 11, RGB cameras can be used to remotely monitor respiration by recording the user's face or forehead. [171]. To record respiratory data from a video of the face, each proposed technique must follow the procedures presented next:

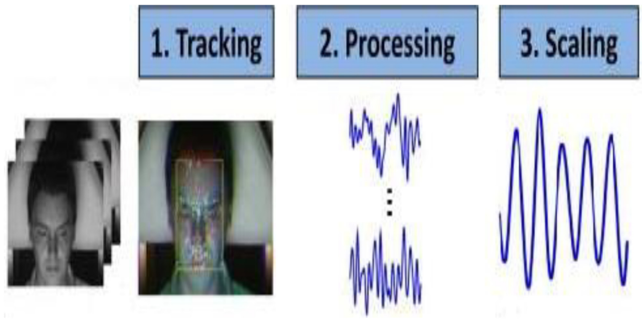

Fig. 11. RGB camera based face and forehead tracking. Figure adapted from Selvaraju et al. [178].

Table 8. Summary of Face and Forehead Tracking Based Sensing Methods

Motion artifacts	High
Environmental effects	High
Sensor size	Low
Cost	Low
Accuracy	Low
LOS/NLOS	NLOS

(1) *ROI selection*: The entire face should be selected automatically. The Viola-Jones method is often employed as a face detector [172].
(2) *ROI tracking*: The ROI should be tracked automatically in the video. For this purpose, the Kanade-Lucas-Tomasi algorithm is often employed [173, 174].
(3) *Color domain and channel selection*: Since oxygenated hemoglobin absorbs light differently than surrounding tissue in the green channel, the green channel's information is utilized [175].

Wang et al. [175] determined the author's respiratory parameters by watching a video recording of the author's forehead, and the results were encouraging. Facial video images of 8 subjects were captured through a 6-channel camera, and Rodrigues et al. [176] used a method based on blind source separation to analyze the images. When data was collected, the participants were asked to remain seated and calm while their faces and necks were carefully monitored. A camera recorded 10 adult subjects' facial expressions while standing still or moving quickly. Experiments were carried out on newborns being cared for in a neonatal intensive care unit so that they could assess the efficacy of methods based on RGB signals. Maurya et al. [177] investigated the use of a black-and-white camera to continuously monitor the subject's respiration rate from the face while they were cycling. The extraction of a reliable signal for reconstructing respiratory waveforms can be accomplished by using data obtained from the intensity of the light on the forehead, which was obtained through blind source separation techniques. A summary of the face and forehead tracking based sensing method is provided in Table 8.

Summary. Despite their widespread availability and low cost, RGB cameras used for forehead sensing have some limitations regarding respiration measurement. Only controlled validation was reported in most of the studies. Primarily, the drawbacks of this technique in respiratory illness

Table 9. Comparison of Various Contactless Methods

Sensing method	ROI	Environment	Comfort	Application
Chest movement sensing	Chest/Abdomen	Static	High	Domestic
Respiratory sound	Mouth	Dynamic	Medium	Domestic
Respiratory air temperature sensing	Mouth/Nostrils	Dynamic	High	Clinical
Face and forehead tracking	Face/Forehead	Dynamic	High	Domestic

come from the following three requirements: continuous illumination of the face, the need to reduce the influence of skin color on raw data, and the necessity to restrict unrelated body movements to respiration. The requirement is to track the face to decrease breathing-unrelated body motions continuously. In conclusion, using a continuous illumination source is necessary to lighten the face when employing this method. This means that the distance between the user and the camera must be managed. This method cannot be utilized at night or in conditions with low levels of available temperature and light, resulting in higher accuracy. A comparison of various contactless sensing methods is provided in Table 9.

4 CONCLUSION

This study investigated contactless methods by exploiting wireless communication sensing for diagnosing and monitoring respiratory illness. Contactless methods have several advantages over contact-based methods, including accuracy and improved patient comfort, which is especially important for long-term monitoring. Contactless methods are less sensitive to environmental factors like temperature and light, resulting in higher accuracy. However, contactless technologies may also have drawbacks and limitations. The impact of ambient influences on raw data varies greatly among contactless approaches, particularly for sensors not explicitly designed for respiratory monitoring (RF, smartphones, camera sensors, etc.). In addition, most contactless systems are hampered by body artifacts, particularly when ROI is required for assessment; however, ROI sensing using advanced signal processing can potentially improve the overall efficiency of the approaches. This study examined four contactless methods for detecting respiratory diseases. Each technique's operating principle and primary characteristics were presented (e.g., real-time monitoring, cost, susceptibility to body motion artifacts). The article also presented open research challenges for diagnosing and monitoring respiratory illnesses using wireless communication sensing.

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Received 8 January 2023; revised 27 August 2023; accepted 31 January 2024