A survey on vital signs monitoring based on Wi-Fi CSI data

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ABSTRACT

The COVID-19 pandemic further highlighted the need to use low-cost remote monitoring procedures for medical patients. Since the results reported in the literature have shown that the use of Channel State Information (CSI) from Wi-Fi networks to remotely monitor patients can provide means to obtain a powerful medical information package in a non-invasive way and at low cost, a consistent review and analysis of the state of the art on this applied technique is developed in the present work. Initially, a mathematical overview of the CSI technology and its functional model is done. Subsequently, details about the technical approach necessary to use CSI in medical applications and a summary of the studies reported in the literature with such applications are presented. Based on the analyses and discussions carried out throughout this work, a better understanding of the current state of the art is achieved. Challenges and perspectives for future research are also highlighted.

1. Introduction

Several medical devices have been used to help monitor, diagnose, and treat many diseases. These devices usually provide an internal or external communication link to allow monitoring, configuration, control, or even remote exchange of information in real-time. The continuous monitoring of the patient's health offers a better knowledge of his/her condition and allows a better flow of information for supervision, treatment, and recovery [1]. Due to the Covid-19 pandemic, we have been facing an increasing number of patients that demand healthcare. As it is a highly contagious and sometimes lethal disease, the monitoring of patients should be as contactless as possible. The healthcare professionals who treat Covid-19 patients need to use personal protective equipment to minimize the risk of contagion [2,3].

Several proposals have been studied in the literature for contactless patient monitoring aiming to deal with this demand. In [4] for example, the authors proposed to use Frequency Modulated Carrier Wave (FMCW) technology to detect human activities through radio frequency signals. However, FMCW has a high cost, which makes this technology not accessible to all. Another possible solution for contactless patient monitoring is the use of Radio Frequency Identification (RFID) technology [5]. RFID is an interesting approach, but it depends on RFID tags to be connected to patients. Therefore, the search for a new and less expensive approach without using invasive devices has shown that Wi-Fi radio signals can be used to track human activities, movements, and vital signs [6,7].

Nowadays, Wi-Fi devices are available in almost every medical and residential environment. Wi-Fi technology is widespread, and applying this technology for health monitoring is non-invasive and low cost. The electromagnetic waves of Wi-Fi signals have the particularity of crossing walls, and do not even require a transmission with line of sight to the patient.

Radio signals (electromagnetic waves) can be used to track human activities. The radio waves are affected by human movements changing the characteristics of the received waves [8,9]. These changes can be recognized in a data set called Channel State Information (CSI). CSI provides channel status information at the physical (PHY) layer such as amplitude, phase, and/or Received Signal Strength Indicator (RSSI) for each subcarrier involved in the multicarrier transmission [10,11]. Current Wi-Fi standards, such as 802.11n/ac, use Orthogonal Frequency Division Multiplexing (OFDM) modulation at the physical layer. OFDM is a modulation technique that divides the transmission frequency band into several subbands, also called subcarriers. Each subcarrier can provide detailed information about the channel state [12]. CSI represents the Channel Frequency Response (CFR) for each subcarrier between the pairs of transmitting and receiving antennas.

CSI can capture how the human body interferes the electromagnetic signal in time, frequency, and spatial domains. This information can be used for different human sensing applications, like human presence detection, motion detection, human identification, fall detection, gesture recognition, human localization, and health monitoring. For health

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monitoring, OFDM subcarriers are used as multiple sensors to detect a person's physical change. A CSI waveform analysis is performed to detect minimal human body activities such as respiration, heartbeat, and others [9,12,13].

In the literature, several studies emphasize the use of CSI as a technology accessible to all for monitoring human activities [6,7,10,11]. In addition, CSI is considered a non-invasive tool for the patient, which generates greater acceptance of its use.

Many survey papers have been published with the focus on comparing different wireless sensing technologies [6,10,14], behavior recognition [7,11], and localization [15,16]. In [14], the authors focused on reviewing the differences between CSI from Wi-Fi devices (Wi-Fi CSI), RFID, and backscatter. The authors of [10] analyzed the key components and core characteristics of the system architecture of human behavior recognition. In [6] the authors presented a review of signal processing techniques, algorithms, applications, and performance results. Yousefi et al. [7] presented the advances in passive human behavior recognition. In [11] the authors surveyed the existing wireless sensing systems in terms of their basic principles, techniques, and system structures. Xiao et al. [15] also gives a survey on both device-free and device-based indoor localization, and [16] presented a survey on localization with emphasis on the basic principles and future trends. The latter also highlighted the differences between CSI and RSSI in terms of network layering, time resolution, frequency resolution, stability, and accessibility.

Different from existing works, this survey focuses on the analysis of CSI data for monitoring human vital signs. It discusses detection, recognition, and estimation techniques that can help achieving this goal. This survey gives a comprehensive guideline to adopt CSI for medical purposes under a safe, scalable, and low-cost perspective. Finally, this survey presents future trends and challenges for enhancing existing Wi-Fi sensing capabilities and enabling new Wi-Fi sensing applications for health monitoring.

The remainder of the text is organized as follows. In Section 2, we present the mathematical model of CSI and its current extraction tools. We also show the general architecture of CSI for the detection of human activities. Then, in Section 3, we present several studies found in the literature that address the detection of vital signs, more specifically respiration and heart rate. In addition, some applications using CSI are presented. In Section 4, we present challenges and perspectives for the use of CSI in healthcare. Finally, Section 5 brings our final remarks.

2. Wi-Fi CSI overview

This section presents an overview of how CSI data is obtained from Wi-Fi devices and how it can be processed and used in some applications. Fig. 1 (adapted from [6]) shows the general architecture of the system used for collection, treatment, and estimation of human activities using Wi-Fi CSI data.

In general, the CSI collection process is carried out by a device equipped with network interface card (NIC). Then, the chosen suitable base signal such as amplitude and/or phase must be extracted from the collected information. The extracted signal feeds the signal preprocessing module in a next step. In this phase, in order to remove out the noise of the signal and obtain more accurate CSI data, preprocessing approaches become essential. It is performed through noise reduction, signal transformation, and filtering techniques [6,8,9]. This paper presents some of the most used techniques to obtain precise CSI data. After signal pre-processing, an analysis of human activities through theoretical modeling-based algorithms and/or learning-based algorithms follows. The modeling-based algorithm usually utilizes typical models, such as Fresnel zone model and angle-of-arrival (AoA). The modeling-based approach faces challenges on building a model. The learning-based approach is mostly used in movement identification applications. Despite requiring a training stage, it can achieve good performance. Finally, the application can detect, estimate, or recognize some human activities and vital signs [6,17,18].
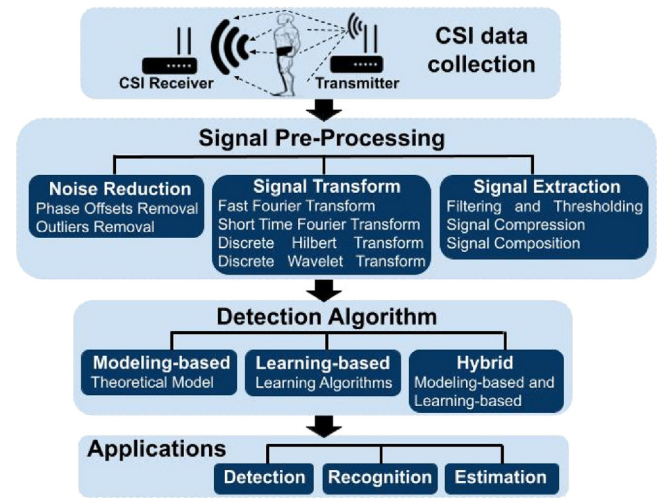

Fig. 1. Wi-Fi CSI system framework.

In short, the architecture shown in Fig. 1 gives a general overview of the CSI-based structure for vital signs monitoring. A more detailed analysis is presented in the following sections.

2.1. Mathematical modeling

In this section, we present a mathematical model of the system used to collect the CSI data.

While propagating in a wireless channel we can observe that the signal reflects on the obstacles. Thus, the received signal is composed by an overlay of multiple copies of the signal which travel over different paths, that is what we call the multipath effect. The signal undergoes changes as a consequence of the multipath channel such as time delay, amplitude attenuation, and phase shift. These changes can be expressed in the form of the channel impulse response (CIR) defined in the time domain, and/or the channel frequency response (CFR) defined in the frequency domain. The CIR can be mathematically described as:

$$h(t) = \sum_{i=1}^{I} a_i e^{-j\theta_i} \delta(t - \tau_i), \tag{1}$$

where a_i represents the attenuation, θ_i the initial phase offset, and τ_i the delay of the ith path. Also, I is the number of paths.

In the IEEE 802.11g/n/ac specification [19–21], the physical layer of Wi-Fi communication systems uses orthogonal frequency division multiplexing (OFDM) technique for both 2.4 GHz and 5 GHz frequency bands. OFDM is a modulation technique that uses a pre-defined number of orthogonal subcarriers [22]. In addition, information can be independently transmitted over different OFDM symbols. The OFDM features make it a good solution for multipath channels and also for multiple-input multiple-output (MIMO) systems.

In the frequency domain, the narrowband flat fading channel model of MIMO system is given by:

$$Y = \mathbf{H}X + N, \tag{2}$$

where $Y \in \mathbb{C}^{n \times n_{sc}}$ and $X \in \mathbb{C}^{m \times n_{sc}}$ represent the received and transmitted OFDM symbols respectively, with m transmitting antennas, n receiving antennas and n_{sc} subcarriers. $\mathbf{H} \in \mathbb{C}^{n \times m}$ is a complex matrix that contains the CSI, and $N \in \mathbb{C}^{n \times n_{sc}}$ represents the noise [12].

To measure CSI, the Wi-Fi transmitter sends Long Training Fields (LTFs), which contain predefined information in each subcarrier, in the frame preamble. The Wi-Fi receiver estimates the matrix (**H**) that contains the CSI information, using the received signal and the transmitted LTFs.

Table 1
Tools for CSI data extraction.

Tool	Supported Chipsets	Max. BW	Technology
Linux 802.11n CSI Tool [24]	IWL5300	40 MHz	802.11n
Atheros CSI Tool [25]	AR9580, AR9590 AR9344, QCA9558	40 MHz	802.11n
OpenFWWF CSI Tool [26]	BCM4318	20 MHz	802.11g
Nexmon CSI Extractor [27]	BCM4365, 66 BCM4339, 58, 455	80 MHz	802.11ac
GNU Radio [28]	USRP B200	80 MHz	802.11ac
Wi-ESP [29]	ESP32	40 MHz	802.11n

Considering a MIMO Wi-Fi system operating under IEEE 802.11n specification, and with m transmitting antennas and n receiving antennas, the signal that contains the estimated CSI of each data streams can be mathematically expressed as

$$\mathbf{H} = \begin{pmatrix} \boldsymbol{h}_{1,1} & \boldsymbol{h}_{1,2} & \dots & \boldsymbol{h}_{1,n} \\ \boldsymbol{h}_{2,1} & \boldsymbol{h}_{2,2} & \dots & \boldsymbol{h}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{h}_{m,1} & \boldsymbol{h}_{m,2} & \dots & \boldsymbol{h}_{m,n} \end{pmatrix}, \tag{3}$$

where $\boldsymbol{h}_{i,j}$ represents the CSI between the ith transmission antenna and the jth receiving antenna. Let c be the number of subcarriers used to estimate the CSI, thus, the state information of the channel established between a pair of antenna (i,j), defined by $\boldsymbol{h}_{i,j} \in \mathbb{C}^{(c\times1)}$, can be mathematically represented by a vector with c elements. We use $\boldsymbol{h}$ to represent a generic $\boldsymbol{h}_{i,j}$ as

$$\boldsymbol{h} = \begin{bmatrix} h_1, h_2, \dots, h_c \end{bmatrix}^{\mathrm{T}}. \tag{4}$$

The analysis using Wi-Fi CSI can provide more information than RSSI since the matrix of collected data is similar to a digital image with a high spatial resolution.

2.2. CSI data collection tools

After presenting the mathematical model of how CSI data is obtained, in this section, we briefly describe some tools used to capture and collect CSI data. Multiple tools have been proposed in the literature to access the CSI on network cards of Wi-Fi devices. Table 1 summarizes some of the most known tools [23].

Linux 802.11n CSITool is a extraction tool that use Intel Wi-Fi Wireless Link 5300 802.11n MIMO radio. It is a modified firmware that includes all the proper procedures for capturing, collecting, and analyzing the CSI data of a wireless channel using an open-source Linux wireless network driver. This tool includes all the software and scripts necessary to run experiments, read, and analyze channel measurements, which makes it a good alternative for health monitoring through Wi-Fi CSI. The chipset IWL5300 provides 802.11n channel state information in a format that reports the channel matrices and each channel matrix entry is a complex number, with signed 8 bits resolution for the real and imaginary parts. It specifies the gain and phase change of the path between a single transmit–receive antenna pair.

Atheros-CSI-Tool is another tool for capturing, collecting, and analyzing CSI data. It allows extraction of detailed wireless communication information from Atheros Wi-Fi network cards. Atheros-CSI-Tool is a modified firmware on an open-source Linux kernel that supports 802.11n chips, and works on various Linux distributions, for example, Ubuntu, OpenWRT, and Linino. Therefore, it is available for personal computers, embedded devices such as Wi-Fi routers, and IoT (Internet of Things) devices.

OpenFWWF CSI Tool (Open FirmWare for Wi-Fi networks) is a project focused on providing a complete and economical platform

to implement new medium access control (MAC) protocols in which it is easier to perform tests. It also offers open-source firmware for Broadcom chips and adopts a reverse engineering method to obtain CSI data.

Nexmon was proposed to enable researchers access to lower-layer frame processing and advanced physical-layer functionalities. It is a C-based firmware for Broadcom/Cypress Wi-Fi chips that mainly focuses on enabling monitoring mode for CSI data extraction. It allows the extraction of information from wireless communication channels between two Wi-Fi devices. Nexmon CSI works on Wi-Fi MIMO devices with up to 80 MHz bandwidth, besides it is compatible with 802.11a/n/ac standards. It can be used on mobile devices (smartphones) and on cheap devices such as Raspberries.

GNU Radio is an open-source software that allows the graphical development of signal processing modules. It is used without specific hardware in a simulated way, or with external RF hardware such as USRP. The USRP is designed for RF applications from DC to 6 GHz, including MIMO systems. Examples of application areas include mobile phones, public safety, spectrum monitoring, radio networks, cognitive radio, satellite navigation, and ham radio. Spectrum monitoring is how GNU radio and USRP are used to collect, extract, and analyze CSI data.

ESP32 was created by Espressif Systems. It is a low-cost, and low-power system with a series of integrated chips with features like dual-mode Wi-Fi and Bluetooth. It is an ideal integrated board for the development of mobile applications, IoT, wearable, among others. Regarding its wireless card, it supports several technologies such as 802.11b/g/n. In addition, it supports bandwidths of up to 40 MHz. This indicates that it can obtain CSI information for at least 128 subcarriers. Wi-ESP developers claim that ESP32 can support up to 16 antennas via an external antenna switch, indicating that more CSI information can be obtained.

2.3. Signal pre-processing

Following the architecture presented in Fig. 1, in stage 2 the signal into equal segments and calculates the FFT in each independent segment, Discrete Hilbert Transform (DHT) that incorporates a phase shift and is useful to find instantaneous changes in a given time within the signal, and Discrete Wave Transform (DWT) [30–33] which provides good resolution of the captured signal.

Signal Extraction is the last step within signal pre-processing. It can be performed by filtering and thresholding the signal, where the high-pass [34], low-pass [35], and band-pass filters [36] are widely used to extract signals with certain dominant frequencies. **Signal Comprehension** is important to reduce signals to a few or a dimension that represents the enormous amount of captured signals. For doing this, some of the used techniques include Principal Component Analysis (PCA) [37], Independent Component Analysis (ICA) [38,39], Singular Value Decomposition (SVD) [33], Self/Cross Correlation, Euclidean Distance, Distribution Function, among others.

Finally, **Signal Composition** is a technique used to estimate or detect a phenomenon using various devices or frequency band characteristics. Some Wi-Fi detection applications require CSI from multiple peripherals, carrier bands, data packets, etc. for a good accuracy. We can cite, for example, SpotFi [40], which requires CSI from several Wi-Fi devices and data packets to accurately estimate AoA and ToF considering decimeter localization precision. Also, in Chronos [41], the authors proposed a system that requires multiple frequency bands for decimeter-level localization using a single Wi-Fi access point (AP). These proposals exemplify the need of a signal composition stage to be able to achieve their goals.

2.4. Detection algorithms

The third stage of the architecture presented in Fig. 1 is the usage of detection algorithms. Three groups of different algorithms can be used in this stage: modeling-based, learning-based, and hybrid. **Modeling-based** algorithms are supported by physical theory such as signal analysis models. For this analysis, the signal obtained from the pre-processing stage is analyzed and the effects produced on the contained CSI information through various phenomena are examined. For example, the CSI amplitude attenuation and the phase shift can be affected by the distance between the transmitter and the receiver and multipath effects including radio reflection, refraction, diffraction, absorption, polarization, and scattering [28,30,32,34–36,42–50]. Within the modeling-based algorithms there are statistical models, based on empirical measurements or probabilities, such as the model used to determine the state of the wireless channel (Power Spectral Density, Coherence Time/Frequency, Self/Cross Correlation, so on) [31,32,39, 43,48,51,52]. These types of algorithms are widely used for estimating human vital signs.

Another group of used algorithms is the **Learning-based** group. Learning-based algorithms are mainly used for recognition of human gestures, position, and detection of people. Learning is carried out using the previous training set of CSI, where the effect of the phenomenon to be detected is reflected in the CSI. Some of the most used algorithms are: Naive Bayes, k Nearest Neighbor, Support Vector Machine, Convolutional/Recurrent Neural Network, and Long Short-Term Memory [12,39,45,53].

On the other hand, the fusion of algorithms has led to the use of **Hybrid Algorithms**. Hybrid Algorithms combine the benefits of modeling-based algorithms and learning-based algorithms. This combination can be beneficial for the development of more robust and complete detection. Studies that use hybrid algorithms include [45,54–57].

3. Wi-Fi CSI applications

Several studies related to different human activities apply the CSI analysis for detection, recognition, and estimation [8,9,13,17,18]. Those work can serve as a starting point to develop health monitoring applications, leading to a robust system for detecting and monitoring vital signs.

For example, in [9], the authors proposed a system called EmoSense to detect human emotions. EmoSense analyzes the time and frequency fingerprints in wireless channel data induced by the physical expression of emotion. In [8] the authors proposed a system called MoSense to detect the movements that are critical indicators of human presence and human activities. Also, in [17], a radioelectric tomography was proposed to detect people and the passage of water. Another approach was carried out in [18], where the authors proposed a system called WiDriver to monitor the activities of a heavy vehicle driver. Activities such as steering wheel movements, answering phone calls, and writing text messages on a cell phone were detected. More recently, in [13], the authors tackled various human activities such as walking, sitting, standing, and running.

CSI has a high potential of becoming a powerful and promising technology to monitor the physical aspects of the environment in general. In this survey, we focus on using CSI to monitor human vital signs. These vital signs are classified mainly in (i) respiration rate, which is the number of breaths that a person takes per minute; (ii) heart rate, which is the number of times the heart beats or contracts during a certain period of time, generally one minute (bpm). These two vital signs, counted in a number of breaths or beats, offer important information to determine the patient current health state. It is worth mentioning that we can find in the literature several studies to detect, recognize, and estimate these vital signs. The Wi-Fi CSI based techniques for

monitoring vital signs become more appealing due to their low-cost, contact-free and easy-to-deploy properties.

This section describes studies that use Wi-Fi CSI to monitor vital signs. For this purpose, we highlight the monitored vital signs and the application relevant features, real-time or non real-time, and multi-person, or single-person, as displayed in Fig. 2. In the following sections, the vital signs monitoring applications are described, the techniques used in the signal processing and modeling are classified according to the classification introduced in Section 2.

3.1. Respiration rate monitoring

Many studies turn to CSI for monitoring the vital signs of a patient. To the best of our knowledge, WiSleep [33] was the first work to detect human respiration rate for sleep monitoring based on CSI using commodity Wi-Fi devices. The proposed device-free approach has the potential to be widely deployed in home and many other clinical and non-clinical environments.

Since then, several studies have been developed in an attempt to improve breath rate monitoring using Wi-Fi CSI signals. In [43] for example, the authors first introduced the Fresnel model in free space, then they verified the Fresnel model for Wi-Fi radio propagation in an indoor environment. They developed a theory to relate one's respiration depth, location, and orientation to the detectability of respiration. With the developed theory, not only does when and why human respiration is detectable using Wi-Fi devices become clear, but it also sheds light on understanding the physical limit and the foundation of Wi-Fi based sensing systems. Along the same line of reasoning, the authors of [46] compared the pattern-based and modeling-based approaches to monitor the respiration rate. They proposed to expand the sensing range of the used Fresnel Zone (FZ) model to the vast regions outside of the first Fresnel zone. They showed the superiority of the Fresnel Zone model-based human sensing over pattern-based approaches, and argued that the Fresnel Zone model-based approaches have great potential in achieving centimeter and even millimeter scale in human activity sensing, enabling a wide spectrum of applications. Besides, the authors in [42] also used the Fresnel Zone model, and showed how a centimeter-scale position change affects the respiration detection performance.

Also with the focus on the Fresnel Zone model, the authors of [36], utilized the Fresnel diffraction model to accurately quantify the relationship between the diffraction gain and the human target's subtle chest displacement and thus successfully turn the previously considered destructive obstruction diffraction in the First Fresnel Zone (FFZ) into beneficial sensing capability. They were able to present the detailed heatmap of the sensing capability at each location inside the FFZ to guide the respiration sensing so users clearly know where are the proper positions for respiration monitoring and if located at a bad position, how to move just slightly to reach a good position.

Another system, called BreathTrack, was proposed in [34] to track the state of human respiration using CSI Wi-Fi signals. They proposed hardware and software correction methods to remove both the time-invariant and time-variant phase distortions (e.g., Carrier Frequency Offset (CFO), Sampling Frequency Offset (SFO), Packet Detection Delay (PDD), and PLL Phase Offset (PPO)), and thus obtain accurate CSI. They also proposed a joint Angle of Arrival (AoA)-Time of Flight (ToF) sparse recovery method to obtain the corresponding complex attenuation coefficient, eliminate the multipath effect in the indoor environment, and extract the information of the dominant path to track the status of breath. Also, regarding the phase of Wi-Fi signals, the authors of [47] discovered that its amplitude and phase are perfectly complementary to each other. They revealed the mathematical model behind and exploited the complementary nature to design and implement a real-time respiration detection system with commodity Wi-Fi devices. They have also used the Fresnel Zone model. Besides, the authors of [45] used the CSI phase difference to intelligently estimate respiration rates
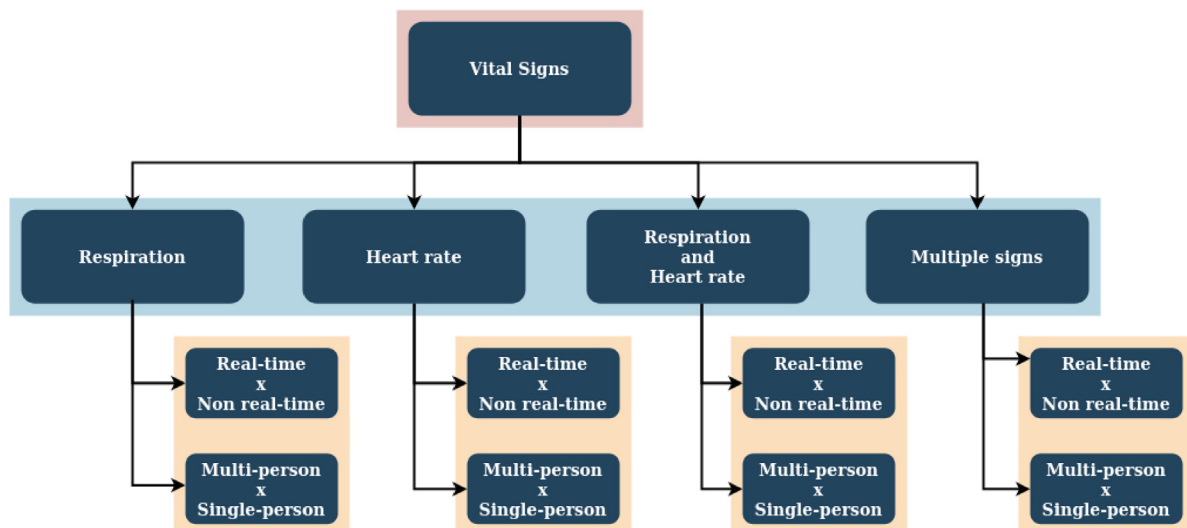
Fig. 2. Vital signs applications diagram.

for multiple people with commodity Wi-Fi devices. At first CSI phase difference data between pairs of antennas at the Wi-Fi receiver were used to create CSI tensors. Then, the Canonical Polyadic Decomposition (CPD) was applied to obtain the desired respiration signs.

In another approach, the authors of [30] explored the detection of multiple persons' respiration at a time. For mitigating the effect caused by other people, they put a receiver besides each user, then they filtered out the data whose Time of Arrival (ToA) was bigger than a truncation threshold. Also with the focus on multiple people, in [51], the authors introduced TR-BREATH, a time-reversal (TR)-based breathing monitoring system. It is capable of respiration detection and multi-person respiration rate estimation within a short period of time. TR-BREATH projects CSIs into the TR resonating strength (TRRS) feature space and analyzes the TRRS using the Root-MUSIC and affinity propagation algorithms to magnify the CSI variations. If respiration is detected, TR-BREATH estimates the multi-person respiration rates via affinity propagation, likelihood assignment, and cluster merging. Besides, it can estimate the number of people in the room with an error of around 1, which is assumed to be known in advance in previous work.

The MultiSense system [38] was developed to robustly and continuously sense the detailed respiration patterns of multiple persons, even if they have very similar respiration rates and are physically closely located. The commodity Wi-Fi hardware nowadays is usually equipped with multiple antennas. Thus, each individual antenna can receive a different mix copy of signals reflected from multiple persons. They successfully proved that the reflected signals are linearly mixed at each antenna and proposed to model the multi-person respiration sensing as a Blind Source Separation (BSS) problem. Then, they solved it using ICA to separate the mixed signal and obtain the reparation information of each person.

In [44], the authors further used the variation of the Doppler spectral energy extracted from the CSI collected by Wi-Fi devices to track the chest displacement induced by respiration. The respiration sign is extracted from the accumulated spectral energy change of Doppler shift at zero frequency according to the periodicity of respiration action.

The FarSense proposal, introduced in [58], presents the first real-time system that can reliably monitor human respiration when the target is far away (within 8 m) from the Wi-Fi transceiver pair, bridging the gap between lab prototype and real-life deployment. The authors proposed a method called CSI-ratio that establishes the corresponding relationship between human movement and CSI-ratio, based on the amplitude and phase of the signal.

More recently, a system called Wi-COVID, was introduced in [37]. It is a non-invasive and non-wearable technology to monitor patients

and track respiration rate for the healthcare provider. The authors explored the possibility of using the Wi-Fi based technology to monitor diagnosed COVID-19 patients who are performing self-isolation in real-time. They proposed the use of a low-cost Raspberry Pi to act as a CSI data collector on the Wi-Fi network. On the software side, they used open-source codes for implementing the CSI processing in a Raspberry Pi. In [37] the authors used Nexmon to extract CSI of OFDM-modulated Wi-Fi frame 802.11n on a per frame basis with up to 80 MHz bandwidth on the Broadcom Wi-Fi chip of a Raspberry Pi. Thus, their implementation was simpler than others as they only needed an off-the-shelf Wi-Fi router and a Raspberry Pi.

Some recent works using the Nexmon firmware for respiratory detection are presented in [54,59]. In [54], the authors show a signal reflection model in a non-line-of-sight NLoS environment called Wi-Phone. They use Nexmon inside a smartphone to capture and process the signals that are reflected in an environment in which the patient does not have a line of sight with the Router or Access Point of the Wi-Fi network. This processing yields breathing patterns obtained from the signals reflected in the environment. In [59], they use a smartphone with Nexmon firmware to estimate a respiration rate. The authors use a selection of optimal subcarriers based on a Fresnel zone model. The model is used to estimate breathing in scenarios with one and several people at the same time.

In Table 2, we present a summary and comparison of the cited studies on breath monitoring by using Wi-Fi CSI analysis together with their own characteristics. We present the used signal processing tools such as noise filtering (NF), signal transform (ST), and signal extraction (SE) tools. Details of which algorithms use which signal processing techniques and for which Wi-Fi sensing applications they are used are also discussed. We also compare whether the operation is performed in real-time or not.

From Table 2 we can observe that most studies used Linux 802.11n CSI Tool. This fact is due to the nature of the most part of Wi-Fi devices that use Linux. It is worth mentioning that a new proposal has been recently applied to Wi-Fi CSI health monitoring systems using Nexmon. It is a promising technology, since it offers simple usage on devices such as smartphones and Raspberries. Another important point to observe is the real-time implementation. Some studies have been developed with the aim of operating in real-time, which makes them more appropriate to work in real environments. On the other hand, several proposals have high accuracy; especially when only one person is considered in the test environment, and the accuracy decreases with the increase in the number of people. Also, the correct environment settings and the person position influence the accuracy of the proposal, offering the best results when patients are in good position, that is, the First Fresnel Zone.

Table 2
Respiration rate monitoring using Wi-Fi CSI signals.

Ref. year	Extraction tool	Pre-processing	Detection algorithm	Multi-person	Real-time	Performance summary
[42] 2016	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	No	N/A
[43] 2016	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	No	N/A
[36] 2018	Linux 802.11n CSI Tool	Noise Reduction Signal Extraction	Modeling-based	No	No	Accuracy: good positions 98.8%, bad positions 61.5%
[34] 2019	Linux 802.11n CSI Tool	Noise Reduction Signal Extraction	Modeling-based	No	No	Accuracy: over 99%
[44] 2021	Linux 802.11n CSI Tool	Noise Reduction Signal Transform	Modeling-based	No	No	Max. error <0.7 bpm, average errors ≈0.15 bpm
[38] 2020	Linux 802.11n CSI Tool	Signal Extraction	Modeling-based	Yes	No	Error rate of 0.73 bpm (breaths per minute)
[45] 2017	Linux 802.11n CSI Tool	Noise Reduction	Hybrid	Yes	No	Accuracy: 1 person 96% less than 0.5 bpm, 2 and 3 person 93% smaller than 0.5 bpm, and 5 person 62% less than 0.5 bpm
[46] 2017	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	N/A	Median error: 0.09 bpm, 0.15 bpm, 0.06 bpm for three different detectable regions
[30] 2017	Linux 802.11n CSI Tool	Signal Transform	Modeling-based	Yes	Yes	Accuracy: >95% (1 person) >88% (2 persons)
[51] 2017	Linux 802.11n CSI Tool	Signal Transform	Modeling-based	No	Yes	Mean accuracy: single-person NLOS 99%, dozen people LOS 98.65%, 9 people NLOS 98.07%
[47] 2018	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	Yes	Reported accuracy of nearly 100% in LOS
[58] 2019	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	Yes	Reported overall detection rate of nearly 100%; mean absolute error less than 0.3 bpm for breath rate
[37] 2021	Nexmon CSI Extractor	Noise Reduction Signal Extraction	Modeling-based	No	Yes	N/A
[54] 2021	Nexmon CSI Extractor	Noise Reduction Signal Extraction	Hybrid	No	No	N/A
[59] 2022	Nexmon CSI Extractor	Noise Reduction Signal Extraction	Modeling-based	Yes	No	Accuracy: over 93%
[60] 2022	Wi-ESP	Noise Reduction Signal Extraction	Modeling-based	Yes	No	Accuracy between 91% and 99%.
[61] 2020	Linux 802.11n	Signal Transform	Modeling-based	Yes	N/A	Accuracy: 1 person 98.8%, 2 person 98.4%, 3 person 97.5%.
[62] 2021	Linux 802.11n	Signal Transform	Modeling-based	No	Yes	Phase and amplitude based measurements had median percentage errors of 8.5% and 7.4% respectively
[53] 2021	Linux 802.11n	Noise Reduction Signal Extraction	Learning-based	No	N/A	K-nearest neighbor classifier using relief feature selection techniques: 85.12%.

3.2. Heart rate monitoring

Heart rate monitoring is another relevant task in vital signs monitoring. Several studies monitor heart rate and respiration simultaneously, but we have found only one proposal for monitoring heart rate only.

The CardioFi system, proposed in [63], monitors the heart rate via Wi-Fi hardware with omnidirectional antennas. The main challenge was the considerable radio frequency noise that affects Wi-Fi transmissions in real-world environments. CardioFi uses a scheme called Dynamic-Window to observe an anomalous behavior in the signal and discard the signals that do not represent greater sensitivity. Thus, they obtain highly sensitive frequencies. CardioFi was tested in non-line-of-sight scenarios with a low Signal-to-Noise Rate (SNR) and improved its percentile error. This solution considers the monitoring of a person, which can be performed in real time. However, only the architecture used for heart rate estimation is presented, needing to be extended to support a real-time medical application.

3.3. Respiration rate and heart rate monitoring

We can also find in the literature more ambitious work, which have focused not just on breath monitoring, or heart rate monitoring, but both at the same time. For example, in [48] Liu et al. proposed to track both respiration and heart rate during sleep by using off-the-shelf Wi-Fi devices. The developed algorithm makes use of the channel information in both time and frequency domain to estimate respiration and heart rates, and it works well when either individual or two persons are in bed. Also in [52], Liu et al. reused the existing Wi-Fi network to track the respiration and heartbeat concurrently during sleep. The results showed that the proposed system provides an accurate respiration rate and heart rate estimation not only under typical settings, but also covering challenging scenarios including the long distance between the Wi-Fi device and the Access Point (AP), non-line-of-sight (NLOS) situation, and different sleep postures.
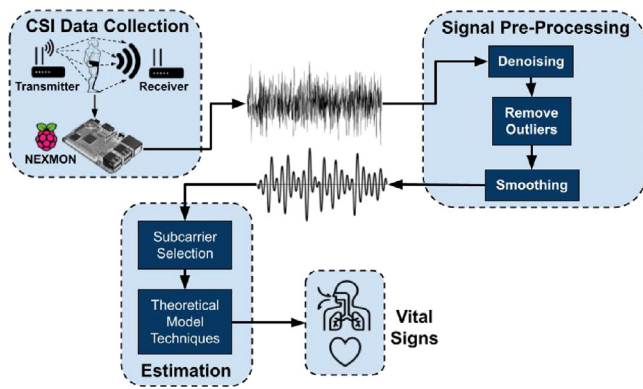
Fig. 3. Practical scheme.

Also following the direction of monitoring multiple vital signs, PhaseBeat [32] leverages CSI phase differences between two receiving antennas on Wi-Fi devices to detect and monitor the respiration rate and heart rate in real-time. The authors discovered that the CSI phase difference data are quite stable after suitable calibration. They also proved that, for indoor multipath environments under small-scale fading, the CSI phase difference data is a periodic signal with the same frequency as the respiration sign when the wireless signal is reflected from the chest of a person. They also showed that PhaseBeat is highly robust for respiration rate estimation under various environments, such as different distances between the transmitter and receiver.

In [35], the authors designed a Wi-Fi signal-based breath and heartbeat recognition system called Wi-Health. They have determined whether or not a human being is alive, and the number of heartbeats and breaths. They also proposed to eliminate similar human activities, which have similar frequency with respiration (0 Hz–1 Hz), such as waving hands. It is necessary to eliminate these activities effectively, otherwise, they may introduce extra peaks in the spectrum and cause inaccurate estimation.

Besides, in [12], the authors proposed a method to recognize and distinguish a person's respiration and heart rate pattern changes by using the Wi-Fi CSI signal. The amplitude of signal waves can represent the periodic up-and-down chest movements caused by respiration and heartbeat, and prominent changes of the signal pattern can be detected by using the Dynamic Time Warping (DTW) algorithm. The authors showed that this method can identify the person's physical status. Besides, they evaluated the method through various experiments with 10 participants.

More recently, another system that detects respiration and heart rate named PhaseBeat was featured in [31]. A rigorous analysis of channel state information phase difference with respect to its stability and periodicity was conducted. They showed that for indoor multipath environments under small-scale fading, the CSI phase difference data are periodic and have the same frequency as the respiration sign when the Wi-Fi signal is reflected from a person chest. Moreover, CSI phase difference is also more robust than RSSI in various deployment scenarios, such as different distances, obstacles/walls, and orientations. In that proposal, the most sensitive subcarrier was selected and processed by DTW to obtain the respiratory sign and the reconstructed cardiac sign. Finally, they applied FFT to measure the respiratory and cardiac rates.

The summary of Wi-Fi based respiration and heartbeat rate applications is shown in Table 3. As we can notice, when the focus is on expanding the vital signs monitored, the most part of research drop off the real time operation. It can be seen that in general the accuracy of the proposals is higher and the average error is lower for respiration rate detection compared to the heart rate detection. Also, most of these studies only consider single-person monitoring.

Likewise, in Fig. 3 we show a practical scheme that exemplifies the process of estimating vital signs (breathing and heart rate). In this example, we start with the collection of CSI data on a common Wi-Fi network, and with the use of a Raspberry Pi device running NEXMON, the CSI data is captured. Notice that other devices and tools for CSI data extraction can be used as shown in Table 1. Once the CSI data is collected, pre-processing is performed since the CSI data may contain noise. To clean the signal, filters are used that eliminate noise, such as the Hampel Filter, or other filters discussed in Section 2.3. Also, outliers are removed and the signal is smoothed with the use of techniques such as the Savitzky–Golay filter, moving average, among others. Next, the vital signs estimation stage begins by making a selection of subcarriers that contain relevant information. This is done by applying signal extraction techniques such as bandpass, lowpass, or highpass filters. In the same sense, signal compression techniques are applied to reduce signals to a smaller dimension that represents the enormous amount of captured signals. A widely used technique is PCA. Finally, we estimate vital signs using signal processing techniques such as FFT, STFT, among others shown in Section 2.4.

3.4. Multiple-signs applications

In addition to the respiration rate and heartbeat, some studies proposed new sensing modalities of human activities such as change in position, micro-movements, tremors, fall detection, among others. The WiSleep [33] proposal, for example, focused on extracting from the CSI rhythmic patterns associated with respiration and abrupt changes due to the body movement. The WiSleep proposal was further extended in [64]. To reliably identify respiration rate in the presence of noise, the respiration is assumed to be periodic. However, an undesirable consequence is that information like abnormal respiration (e.g., sleep apnea) that violates the periodic assumption is not easily identified. Compared with the existing works, the system proposed in [64] can track abnormal respiration (e.g., sleep apnea) and can also provide respiration information when the person is under different sleeping positions.

WiCare [39] system is another example of work that uses Wi-Fi CSI signals to monitor different vital signs in parallel: respiration rate with the coexistence of some micro-motions (e.g., reading, writing, using the phone). More specifically, WiCare is able to distinguish micro-motions of a specific individual from his/her respiration. This approach is based on the fact that respiration results in CSI fluctuations with narrower frequency band compared to that of micro-motions.

In [28] the authors presented a two-dimensional phase extraction system using passive Wi-Fi sensing to monitor three basic elderly care activities including respiration rate, essential tremor, and falls. The entire implementation was performed using software-defined radios, and they also used signal processing techniques to analyze the cross-ambiguity function and identify phase variations in two separate planes.

The authors of [50] proposed a motion detection capability enhancement method based on Rice-K theory and Fresnel theory. Movements such as turning over will affect the accuracy of vital signs monitoring, thus, they also proposed a sleep motion positioning algorithm based on regularity detection for quickly distinguishing such movements.

The difficulty of monitoring multi-person sleeping respiration generally comes from the necessity of separate the effects of multiple persons' respiration. Another problem is that even though the separation can be feasible with some complicated algorithms, it is still really hard to map the multiple identified respiration states to the corresponding persons. For solving this problem, the authors of [49] proposed an approach via the deployment of Wi-Fi transceivers. A carefully placed Wi-Fi transceiver may only be affected by the person in a certain location. Furthermore, they considered the sleeping movements of people as well as the sleeping posture change to improve the robustness of the

Table 3

Respiration rate and heartbeat rate monitoring using Wi-Fi CSI signals.

Ref. year	Extraction tool	Pre-processing	Detection algorithm	Multi-person	Real-time	Performance summary
[48] 2015	Linux 802.11n CSI Tool	Noise Reduction Signal Transform	Hybrid	No	No	Respiration Rate Error: <1.1 bpm (1 person), <1.2 bpm (2 persons); Heart Rate Error: <5 bpm (1 person)
[12] 2018	Linux 802.11n CSI Tool	Signal Transform Signal Extraction	Modeling-based	No	No	Accuracy: respiration rate 94% heart rate about 82%
[52] 2018	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	No	Accuracy: 80% < 0.5 bpm for breath rate, 90% < 4 bpm for heart rate
[31] 2020	Linux 802.11n CSI Tool	Signal Transform	Modeling-based	No	No	Median error of 0.25 breaths per minute (bpm) for respiration rate, and 1.19 bpm for heart rate
[35] 2016	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	No	N/A	Average estimation error under: 0.6 bpm (respiration rate), 6 bpm (heart rate)
[32] 2017	Linux 802.11n CSI Tool	Noise Reduction Signal Transform	Modeling-based	No	Yes	Estimation error: <0.85 bpm (respiration rate), <10 bpm (heart rate)

Table 4

Multiple signs monitoring using Wi-Fi CSI signals.

Ref. year	Extraction tool	Pre-processing	Detection algorithm	Multi-person	Real-time	Extra signal	Performance summary
[64] 2016	Linux 802.11n CSI Tool	Noise Reduction Signal Transform	Modeling-based	No	No	Posture	Respiration Rate Estimation: greater than 85%; Apnea Estimation: 82.1%, Change position over 80%
[39] 2017	Linux 802.11n CSI Tool	Noise Reduction Signal Extraction	Modeling-based	No	No	Micro-movements	Estimation error <2 bpm for 80% of experiments
[33] 2014	Linux 802.11n CSI Tool	Noise Reduction Signal Extraction	Modeling-based	No	Yes	Posture	Respiration Rate Estimation: 85%; Posture change ≈80%
[28] 2017	USRP B200	Signal Transform	Modeling-based	No	Yes	Movement	Accuracy: respiration 87%, detecting falls 98%, tremor classification 93%
[49] 2018	Linux 802.11n CSI Tool	Noise Reduction	Modeling-based	Yes	Yes	Posture	Mean absolute error: Respiration 0.614 bpm in the middle of the FZ, 3.130 bpm in the boundary; Apnea false alarm 6.8%, missed alarm 7.09%
[50] 2021	Linux 802.11n CSI Tool	Noise-reduction	Modeling-based	No	Yes	Posture	96.618% for breath rate and 94.708% for heart rate
[65] 2021	Linux 802.11n CSI Tool	Noise-reduction	Modeling-based	No	Yes	Night movement	The breath rate error varied between 0.34 BPM to more than 5 BPM
[66] 2021	Linux 802.11n CSI Tool and Atheros	Noise Reduction Signal Extraction	Modeling-based	Yes	N/A	Nocturnal seizure	Accuracy: 93.85%
[67] 2021	Linux 802.11n CSI Tool	Noise Reduction Signal Extraction	Modeling-based	No	Yes	Sleep stage	Accuracy: accuracy of 81.8%

system. Thus, they employed the difference between the maximum and minimum value and the variation of the peak amplitude extracted from the frequency domain among the CSI streams of all the subcarriers to detect apnea.

In Table 4, we summarize and compare the cited studies on different vital signs monitoring by using Wi-Fi CSI analysis. We also present some of their characteristics such as signal processing and extraction tools, used model, and performance. We also compare whether the operation is performed in real-time or not. As shown in Table 4, most studies focused on several vital signs monitoring consider also a real-time implementation, and modeled-based detection algorithms. In those ones, the respiration rate detection accuracy is slightly inferior when compared to the single-person detection proposals seen in the previous sections.

4. Challenges and perspectives

Monitoring vital signs and human activity using Wi-Fi CSI can support healthcare applications. However, challenges must be addressed to achieve practical implementation. When referring to vital signs detection, setting scenarios for capturing the CSI is not trivial. The movements and daily activities have a larger impact on the CSI when compared to breathing and heart rate. Therefore, vital signs detection

imposes a strict demand on signal reception and processing. In addition, we face challenges, such as electromagnetic interference, the recognition of simultaneous movements of different body parts, multi-person environments, and non-line-of-sight (NLS) scenarios. This section covers these challenges and addresses perspectives of future applications and improvements of using Wi-Fi CSI for vital signs monitoring.

4.1. Challenges and open issues

The first stage of the CSI architecture is data capture. Here, the antennas placed on the environment for transmitting and receiving Wi-Fi signals vary in quantity and shape. There are scenarios set to use a single antenna to transmit and a single antenna to receive (single input single-output, SISO) in a point-to-point configuration. Another configuration corresponds to MIMO technology, with several antennas used to transmit and receive the CSI data. MIMO configuration are necessarily governed by 802.11n/ac standard. In both configurations, the convergence point is the amount of CSI information captured; the greater the number of antennas or devices involved, the greater the amount of data.

Specifically, the number of devices needed to obtain the necessary information and increase the accuracy of behavior recognition is an issue that needs to be studied. Studies such as Zhu et al. [68], and

Li et al. [69] confirm that increasing the number of Wi-Fi devices can improve system performance. However, increasing the AP density also increases the electromagnetic interference, and increasing client density results in a packet collision increase, if the IEEE 802.11 RTS/CTS mechanism is disabled. This is one of the main challenges when identifying vital signs.

Increasing the number of Wi-Fi devices allows enlarging the coverage area and improving the performance of models based on Fresnel zones for example. However, the Fresnel zones of multiple links are complex [70]. So, how to detect various Fresnel zone boundaries is a big challenge. It is difficult to identify the best transceiver locations and correct orientations [30]. The scenario configuration is a critical step for efficient CSI data collection that allows more precise vital signs detection. In addition, the number of devices depends solely on the amount of information that we are capable to analyze, and if the used tool supports this capture. The CSI data capture tools mentioned in Section 2.2 differ according to the characteristics of the chosen scenario.

A fundamental discussion for CSI capture performance is the line-of-sight (LoS) of antennas and devices. In a scenario where the antennas and devices have a line-of-sight between them and the patient, the captured data is more robust and fully describes the vital signs to be detected. However, in a scenario where the devices and antennas have no line-of-sight (NLoS) between them and neither with the patient, the results of data capture can be insufficient. In NLoS scenarios, the raw phase variation becomes more unstable compared to LoS scenarios; this is mainly due to the extra attenuation in the NLoS scenarios [34]. This makes the detection of vital signs in non-line-of-sight scenarios an important challenge. These consequences occur due to the interference in a LoS be lower than in NLoS setting.

In a scenario with line-of-sight, the detected interference is mainly due to the patient, in whom the signals interfere (reflect, scatter, attenuate, and so on), thus the CSI can be obtained to later infer the vital signs. On the other hand, in a scenario without a line-of-sight, not only the patient generates interference, but also other objects e.g. concrete walls, which can distort the signal and CSI measurements. Consequently, the captured information does not generate adequate reliability for its subsequent treatment and vital signs inference.

Once the CSI data were captured, the next stage is the signal pre-processing. This stage focuses on cleaning the signal as much as possible from external noise. Gaussian, white, thermal, or any other inherent noise in wireless communication are coupled to the signal with the transmitted information. Various types of filters are applied in an attempt to clean the signal, as described in Section 2.3. For further analyzing the signal, filters must be applied to obtain a resulting signal as reliable as possible, thus cleaning the signal becomes a challenge. It is necessary that the cleaned signal defines the most reliable waveforms, i.e. when the respiration frequency is detected, the signal is initially analyzed in an interval of 0.2 Hz to 0.4 Hz, and the wave variation, caused by the patient's chest motion when inhaling or exhaling, can be observed.

After the respiration rate detection, the heart rate detection is carried out, which due to its inherent heartbeat process is represented in less intensity compared to respiration. This cardiac detection can be affected by the respiration rate, as the effect of respiration on the CSI is considerably stronger when compared to the effect of the heartbeat. In breath monitoring, the requirements for signal filtering can be less complex and demanding compared to cardiac monitoring. Cardiac detection requires that the resulting signal display the wave peaks in detail while conserving the small wave distortions (peaks) caused by the heartbeat. That is why it is important to use the most appropriate filtering technique to clean the signal without losing the heartbeat effect on the captured CSI.

The next stage is the detection of vital signs using various algorithms shown in Section 2.4. What we find in the studies presented in the literature is that there are two aspects in the detection of vital signs

or human activities in general. When we talk about detecting a person, recognizing gestures or estimating movements, the proposed studies induce the use of artificial intelligence algorithms, specifically machine learning. However, when we refer to the detection of vital signs, the techniques involved are based on theoretical models. This is because, as described above, when we detect vital signs such as heart rate, it is necessary that the waveforms (peaks) are detailed as clearly as possible, and for this, theoretical signal modeling techniques present good performance. However, the lack of studies that use machine learning algorithms to detect vital signs leads us to thinking about how well they might perform for this type of detection. We start from the point that, for example, for heart rate detection, the peaks produced by the beats that affect the captured signal represent distortion patterns, then these patterns could be identified by a machine learning algorithm as a recurrence throughout monitoring, whereby the actual value of the heart rate can be determined. In summary, at this stage the use of theoretical signal modeling techniques and machine learning algorithms for the detection of vital signs varies according to the final detection purpose. Likewise, the used algorithms and/or techniques have a different behavior depending on the vital sign detected, which unleashes a need for standardization of detection techniques or algorithms.

Detection of vital signs results in a challenging task, mainly due to the simultaneous movements of different parts of the body and/or the presence of several people in the same environment. Commonly people perform multiple movements simultaneously and the collected CSI contains the resulting mixed effect of all those moves. Distinguishing the signal change caused by each movement of the body is the basis for ensuring the best performance in detecting vital signs. However, the simultaneous detection of body movements is a challenge to be faced. On the other hand, some studies as TR-BREATH [30,71] have shown that the increase in the number of users generally decreases the recognition accuracy. It is also important to identify the presence of several people in the same environment and eventually be able to differentiate the effect of each person on the CSI. In this way, it would be possible to monitor more than one person at the same time. Also, avoiding interference by other people in the vital signs of the patient being monitored. However multi-person behavior recognition becomes a challenge as the number of people increases.

Finally, the last stage of application leads to the detection, estimation, or recognition of some human activity. In the health field, it is necessary that detection be taken as the main application. This application leads to the detection of vital signs of people/patients. One of the perspectives is that the detection of vital signs must be carried out continuously, in real time. This ongoing evaluation is done for the purpose of providing up-to-date medical information about the patient to medical staff and making better decisions for the benefit of the patient. Studies in the literature lack this adaptation of real-time continuous detection and do not provide an applied approach to the detection of vital signs. Also, new challenges such as security, scalability, reliability and portability of detection information arise and can generate complications in the continuous detection of vital signs. These challenges emerge throughout the detection process and the inherent wireless scenario, where detection takes place. Thus, security can be affected in data capture since it is carried out in a wireless environment. It may be subject to malicious attacks that can distort captured CSI data.

Security can be improved by incorporating CSI with upper layers such as Transport Layer Security (TLS), Secure Sockets Layer (SSL), application layer, and user like suggested in [72]. Regarding scalability, there are two important points to address. First, the studies found in the literature that address the estimation of vital signs in two or more people in the same environment are still poor. The need to find new solutions that support or differentiate with better accuracy the vital signs of a group of individuals and not just one, as is currently being done, is an important approach. Second, the growth of devices that collect, process, and estimate vital signs in various environments is still

almost null. The need arises to develop an architecture that supports this topology of CSI collector devices. In most jobs, only a single device that collects CSI data is used in a single environment. So, if we think of a healthy environment, it would be interesting for this CSI data collection to be carried out massively in various environments and that this incorporation of several CSI devices does not generate problems at the network level, CSI data collection and even processing.

In the area of reliability, the information obtained by the treating physician may not be reliable or even non-contiguous. Considering portability, the need for monitoring equipment (antennas, devices) to be as portable as possible for coupling to different types of applications is crucial. In the same way, the final applications must be coupled to the information provided by these monitoring devices. Therefore, the problems and challenges increase as new elements are added to the detection of vital signs. It is important to overcome these challenges and propose technologies that work in conjunction with the detection of vital signs and return a robust medical system that uses CSI technology, but without affecting its initial purpose, which is the vital signs detection for medical applications.

4.2. Future directions

Real-time monitoring allows reducing the risk in life-threatening. When a patient faces a life-threatening situation, it can be identified immediately and an alert signal can be triggered instantly. So, the patient can receive the necessary medical assistance. Many events as: Human Activity Recognition (HAR), fall detection, respiration and heartbeat detection and even disease diagnosis, are of interest for eHealth applications. One of these events or a combination of some of them can indicate the need for medical help that a person may have. Disease recognition using CSI is the least addressed in the literature and it turns out an interesting open research field [49,64].

For feature extraction and activity classification, Machine Learning (ML) techniques have become a promising alternative. In the literature, among the main ML algorithms used for the detection and recognition of human activity and vital signs are: LSTM [13,73,74], SVM [3,13, 68], k-NN [9], and Backpropagation Neural Network (BPNN) [75–77]. Those studies demonstrate the ability of ML algorithms for detection and recognition of human activity and vital signs, and open the way for new research focused on detecting diseases and improving eHealth applications.

In the literature, studies show that the LSTM algorithm is capable of extracting deep characteristics of the input data automatically without the need to use complex techniques for the treatment of Wi-Fi CSI signals. Therefore, LSTM is considered a good candidate for the classification task in real-time eHealth applications. So, it is an interesting option to use LSTM to perform a deep analysis of respiration and heartbeat sign extracted from CSI signals. Since the phase component of the signal is sensitive to chest movement caused by respiration [78], it is considered that classification algorithms can be used to estimate human respiratory activity and eventually infer or detect respiratory problems, such as sleep apnea.

A combination of detection of human activity and respiration sign, similar to BodyScan [79], is an interesting approach. In BodyScan, since CSI is captured by two designed wearable devices, it does not fit the device-free activity detection classification, which is our main focus. However, that proposal shows good results determining the user's respiration rate when motion is not detected and a body is in a stationary state.

Identifying the effect of common human activities on the CSI may improve vital sign extraction performance. Also, since knowing the activity immediately before an anomaly on the respiration sign and the heartbeat can help the classification and identification of health issues or even a medical emergency. For example, when there is an abnormality in the respiratory sign or heartbeat after a fall or after a long walk. These sign anomalies could be associated with pulmonary deficiency, tachycardia, bradycardia or arrhythmia. In this way, hybrid techniques are an interesting option to improve performance in the detection of vital signs.

In the literature, some studies [9,80] show how sensitive CSI is to small movements in the body and that is possible to detect an analyze fine-grained radio reflections from face movements. The fact that common emotion and expressions of people can be recognized from CSI [9] opens the possibility to also identify expressions associated with pain and thus identify when a person is suffering some pain. Another interesting possibility results in inferring a person's risk of suffering depression when a pattern of sadness becomes repetitive. Furthermore, since it is possible to read the movements of the mouth and know what a person is talking about from CSI, as shown in [80], words or word sequences used by people to request help can be identified. That application may be used to identify a person's request for help with cardiorespiratory attacks, in which the person is unable to emit the sound of speech.

5. Conclusions

This work provided a survey on detecting vital signs using channel state information from common Wi-Fi devices. We presented a general overview of the channel state information, a brief description of the general architecture of a CSI-based system, and its mathematical model. According to the presented techniques, we discussed several studies that mainly deal with the detection of human vital signs such as respiration and heart rate based on CSI. These studies were classified and described according to their signal processing techniques, detection algorithms, application, features as real-time monitoring, or multi-person capabilities, and the performance in the proposed scenarios. These compelling Wi-Fi CSI studies for vital sign monitoring have shown promising performance in various application cenarious. In addition, we also point out the limitations of the current Wi-Fi CSI based vital sign monitoring approaches and show a few challenges yet to be overcome such that CSI analysis can be fully used in practice to monitor vital signs and support a variety of eHealth applications.

Declaration of competing 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.

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