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A review of wearable and unobtrusive sensing technologies for chronic disease management

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ABSTRACT

With the rapidly increasing number of patients with chronic disease, numerous recent studies have put great efforts into achieving long-term health monitoring and patient management. Specifically, chronic diseases including cardiovascular disease, chronic respiratory disease and brain disease can threaten patients' health conditions over a long period of time, thus effecting their daily lives. Vital health parameters, such as heart rate, respiratory rate, SpO_2 and blood pressure, are closely associated with patientsâ€™ conditions. Wearable devices and unobtrusive sensing technologies can detect such parameters in a convenient way and provide timely predictions on health condition deterioration by tracking these biomedical signals and health parameters. In this paper, we review current advancements in wearable devices and unobtrusive sensing technologies that can provides possible tools and technological supports for chronic disease management. Current challenges and future directions of related techniques are addressed accordingly.

1. Introduction

Chronic disease is the world's leading cause of death, accounting for over 60% of all-cause deaths globally [1]. The most common chronic diseases include cardiovascular diseases, diabetes, hypertension, stroke and chronic respiratory disease, affecting the patient physically and mentally [2]. More specifically, 17.9 million people die each year due to cardiovascular diseases according to reported data from the World Health Organization (WHO); this represents approximately 31% of all deaths worldwide. 235 million people suffer from asthma, a common chronic respiratory disease among children. Hypertension, also called high blood pressure, is another lifelong disease that can lead to severe health complications (such as heart disease and stroke) if not properly managed. In addition to the direct influences of symptoms, the chronic diseases also reduce human immunity. People with chronic diseases are fragile to the infectious diseases, leading to more serious comorbidities and complications. The current coronavirus disease-2019 (COVID-19) pandemic is a typical example. Due to its rapid and explosive spread across the globe, COVID-19 has become a severe public health issue, infecting more than 1.5 million people across 210 countries. One study has shown that 48% of COVID-19 patients have pre-existing chronic diseases and are more prone to present severe symptoms. Accordingly, chronic patients need to take extra precautions, including special attention to those specific organs or tissues already in a state of dysfunction.

Since the situation of patients with chronic diseases may worsen suddenly and improve only slowly, long-term health management and monitoring of disease is an effective and necessary approach. Key physiological parameters (e.g., ECG, RR, SpO_2, BP, etc.) are the most essential indicators for evaluating the state of an illness for those chronic diseases in clinical applications, allowing for early diagnoses of suspected cases and providing treatment guidance for doctors. However, it is impossible for patients to receive treatments in hospital over long periods due to the high cost of medical treatment. In response, the ideal scenario is that the physiological parameters of patients can be monitored during their daily activities and transferred to data centers that doctors can access through remote monitoring techniques. However, current remote monitoring using telecommunications technology is of

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limited value when measuring disease progress, as it lacks the important physiological indicators for severity evaluation. Therefore, the use of wearable and unobtrusive monitoring devices, as an important tool to monitor physiological signals in daily life, are necessary for chronic patients to prevent significant deterioration and return to normal life.

Fortunately, the development of wearable and unobtrusive monitoring devices offers a promising solution. In recent years, numerous commercial products have been developed for the monitoring of physiological indicators during daily activities. HeartGuide [4] is the first wearable blood pressure monitor, and has received 510 K FDA clearance as a medical device. It can check BP values through an extra-stiff band that inflates to take an oscillometric measurement [5]. The FDA-approved ZIO patch is an effective wearable patch device for the long-term monitoring of ECG in a comfortable manner and is verified to be better at diagnosing arrhythmias than the Holter monitor [6]. Its design features no wires, batteries or leads, making it more favored to patients. Remote monitoring using wearable and unobtrusive devices can provide early predictions, continuous monitoring and remote diagnosis of chronic diseases in various real-world scenarios. These technologies are convenient to use, with low-cost and minimal interference, and are suitable for large-scale monitoring. Personal data, including all essential physiological parameters, can be monitored effectively, meaning that these technologies can be deployed across almost every application scenario.

The purpose of this study is to review advanced wearable and unobtrusive monitoring technologies for possible applications in remote diagnosis of chronic disease. The structure of this review paper is organized as follows: Section II introduces the wearable devices. Section III describes the unobtrusive monitoring techniques. Section IV lists existing research on early warning and dysfunction detection. Section V discusses challenges and future directions for the development of monitoring techniques.

2. Wearable techniques

Wearable techniques are especially suitable for the long-term monitoring of physiological conditions in chronic patients due to their inherent ease of use and low cost [7,8]. A considerable number of wearable devices have been developed and validated for the monitoring of nearly every kind of vital physiological information. According to the studies on home care for patients with chronic diseases, wearable devices can be used for detecting several commonly observed symptoms and signs of deterioration, including the monitoring of cardiovascular functions and respiration as an urgent need [9,10]. In the case of patients with arrhythmia, heart failure and other cardiovascular disease, online analysis of ECG can monitor the conditions of patients. For example, wearable ECG watches can automatically detect the onset of atrial fibrillation disease [11]. Breathing rate is an important physiological index for detecting chronic respiratory diseases. Once respiration monitoring devices detect abnormal conditions (such as a high or low breathing rate), they trigger a warning that can remind patients to avoid accidents directly and indirectly caused by the disease [12]. The various applications of these wearable devices show promise in greatly reducing the pressure of patients and their families from sudden deterioration of diseases. Our review in this section will illustrate how far modern wearable techniques have come and their potential contributions to practical use. An overview of the techniques involved is given in Fig. 1.

2.1. Wearable devices for monitoring of cardiovascular functions

Cardiovascular diseases, such as coronary heart disease and heart failure, have a high mortality rate and may easily become chronic due to the difficulty of radical treatment, causing serious economic and psychological burdens for patients [13]. Cardiovascular functions are vital physiological indicators of body conditions and have very close connections with symptoms of chronic cardiovascular diseases. As a result,

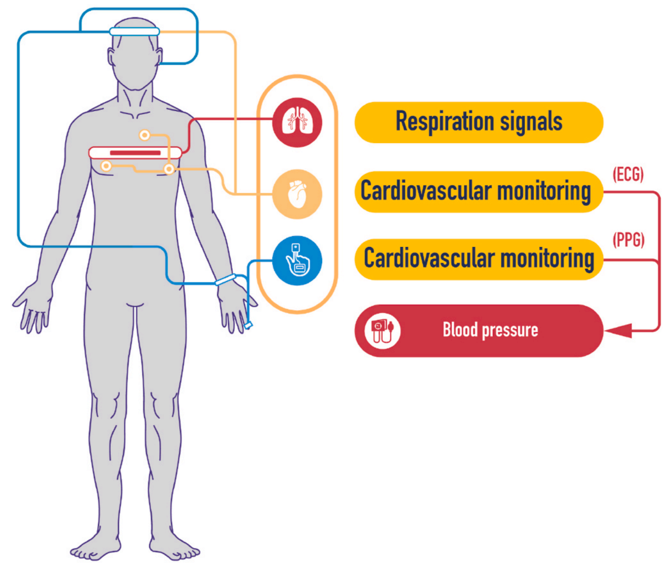

Fig. 1. An overview of the wearable techniques involved for long-term monitoring.

wearable techniques for cardiovascular monitoring have been research hotspots in research for decades. Numerous wearable devices and algorithms have been developed and deployed into the consumer market. The primary clinical indexes, such as heart rate (HR) and heart rate variability (HRV), can be monitored directly using these devices. Other vital features like BP, oxygen saturation of blood (SpO_2) and blood glucose can be derived through indirect measurement and machine learning involved physiological modeling. Early warning and detection of cardiac dysfunction based on these extracted indicators may also contribute to clinical decision-making for diagnosis and treatment.

2.1.1. Measurement

Electrocardiography (ECG) is widely considered the gold standard for heart monitoring. It consists of a projection of cardiac electric activities on the body's surface, measured by the electrical potential difference between two distant points. Many previous studies have proven the robustness of ECG measurements from the torso area, using either chest bands [14] or vests (singlets) [15,16] to attach the electrodes to the skin tightly and comfortably, in both adults and children [7]. Researchers have also been sought other user-friendly solutions through integrating ECG measurement into a variety of daily accessories. An interesting study by Wilhelm et al. attempted to embed ECG electrodes into a helmet for long-term monitoring when riding [17]. Besides, ear-phone styled devices have been proven effective for ECG acquisition and can provide high signal quality under strenuous daily head movement [18,19]. Wristbands (watches) are also widely employed in wearable ECG [20]. Several physiological indicators of ECG (including HR) can easily be measured from two fingers with confidence. However, other diseases such as infarct localization require multi-lead ECG recordings (e.g., ECG vest). The applications of long-term continuous monitoring are largely limited due to their strict measurement requirement. For most wristband styled systems, their capacity for long-term continuous monitoring is weakened by its measurement processs, during which userâ€™s fingers from the contralateral hand should be placed on the band (watch) to form a heart loop. An optimized solution may involve an armband worn on the single side with specially designed electrodes and carefully arranged electrode placement [21]. Fig. 2 lists typical prototypes for wearable ECG monitoring.

Another common concern is the materials used. Unlike conventional ECG systems in which hydrogel electrodes are used, wearable ECG systems usually employ dry metal electrodes or textile electrodes (TEs) [22]. Considering its skin-friendly characteristics, TEs have been

Fig. 2. Prototypes for wearable ECG monitoring: (a) wrist-worn ECG monitor [20]; (b) wearable ECG smart vest system [15]; (c) wearable singlet type with TEs [16]; (d) ear-ECG device [18]; (e) and (f) wearable ECG vest for neonatal monitoring [28,29].

identified as a promising substitute for traditional electrodes.

The effective realization of multi-lead ECG has also attracted special attention in the wearable literature. For instance, integrating the standard 12-lead electrodes into a vest will introduce bundles of cables and connectors, increasing the complexity and size of the designed systems. Recent efforts have been made to resolve this issue by devising textile printed circuits [15] and new analog-signal-compatible communication buses [19].

Photoplethysmography (PPG) is another kind of vital sign, acquired by injecting photons into human body tissues and analyzing the transmitted (transmission-type PPG) or reflected (reflection-type PPG) light [23]. For wearable devices, reflection-type PPG is commonly used as it can be measured from any body part as long as there is sufficient perfusion in the subdermal vascular network [24]. PPG measuring from forehead using a headband has been reported [25], while similar devices can also be in the form of ear-phones [26] or gloves [20] (Fig. 3). Wrist-worn PPG has also raised particular attention in the literature because it can be easily integrated into commercial fitness wristbands (watches) [27].

The major obstacle to using PPG is its relatively low robustness and reliability under strenuous exercise due to motion artifacts [27]. For decades, researchers have been investigating effective solutions, and now a recent study has realized highly accurate average HR extraction

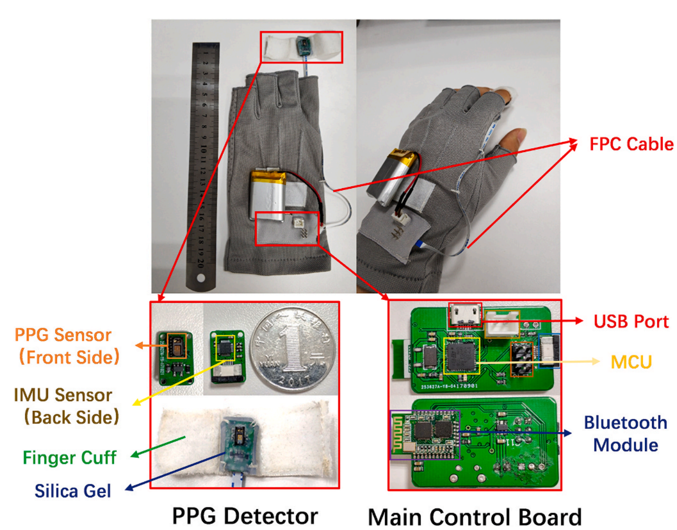

Fig. 3. Glove-style wearable PPG device [30].

[22] and waveform detail recovery [19,30] from corrupt PPG signal, ready for clinical use.

In addition to ECG and PPG, other techniques for decoding the mechanical information of heartbeats have been investigated. Ballistocardiography (BCG) and Phonocardiography (PCG) are two representative approaches [31]. BCG, usually collected from fixed weighing scales or chairs, has been made possible in wearable devices, by introducing highly sensitive accelerometers attached to torso [32]. The potential to embed PCG into wearable devices has also been shown, with reliable heart sound segmentation achieved by practical signal processing approaches [33]. However, both BCG and PCG are prone to environmental artifacts and are thus rarely used in daily living conditions.

There is great promise for all the aforementioned measurements to be applied in abnormality monitoring of chronic cardiovascular diseases. However, the extraction of higher-level physiological parameters and information is required from raw measurement data before practical use can be achieved in clinical scenarios. The following subsections will deal with these concerns.

2.2.2. Physiological parameter extraction

Based on the aforementioned bio-signal measurements, several vital physiological parameters can be derived. Average heart rate (AHR), calculated by counting the number of heartbeats within a certain length of time, is widely used in commercial wearable devices for body-condition evaluation during exercise. AHR can be easily counted from ECG through QRS detection algorithms [15,34], whereas for PPG, the progress of calculating AHR is usually completed by analyzing spectrum features of PPG [27]. HRV is another essential index of body condition that can be acquired by wearable techniques. HRV has been proven a significant indicator for the diagnosis of cardiovascular diseases [35], and shows a strong correlation with the autonomic nervous system dysfunctions and sleep disorders [36]. Typically, the HRV calculation requires N–N intervals from ECG. Recent studies have also indicated that the pulse intervals of PPG, from which the Pulse Rate Variability (PRV) is derived, could also be a promising surrogate for N–N interval detection [37]. The signal quality of PPG measures under static conditions is relatively high. Under such circumstances, linear approaches can be applied for deriving fiducial points. However, deriving pulse intervals from noisy PPG (which is unavoidable in daily-use wearable devices) is not as straightforward as those from ECG (where R peaks can be easily detected even under strenuous activities), because noisy PPG waveforms are usually poorly corrupted by motion artifacts, and fiducial points cannot be discerned correctly. Recent efforts have aimed to recover PPG pulse intervals during daily activities using instantaneous frequency [38], graph theory-based approaches [39], or deep learning-based methods [40].

In addition to HR and HRV, other vital signs can also be derived through physiological modeling, where machine learning is often involved. As a crucial physiological parameters reflecting the health status of patients with cardiovascular diseases [41], BP can be estimated using wearable devices. Thanks to the well-known Pulse Transit Time (PTT) theory, a large number of studies have been completed using the time intervals between ECG and PPG fiducial points, and clinical-level cuff-less continuous BP monitoring can be realized following delicate calibration [42]. Gopal et al. [43] have designed a wearable watch that can provide cuff-less BP estimation. The principle of the device is to compute the PTT by measuring ECG, PPG and tri-axial seismocardiogram to obtain the BP estimation. Peripheral PTT-based method has also been proposed, using more than two PPG sensors to improve user comfort [44], which enables BP monitoring with a single sensing node. Since the coefficients in BP estimation models are subject-dependent and time-variant, calibration issue is another crucial problem to be addressed. Recent trends in this field include long-term calibration-free monitoring using deep recurrent neural networks [45,46]: the resulting algorithm has surpassed the traditional arterial PTT-based method in BP estimation accuracy because single-site PTT measurement on arterioles using multi-wavelength PPG shows a good correlation with BP [47].

SpO_2 is another important physiological parameter that can be extracted from wearable PPG. The principle of SpO_2, which uses a linear approximation of Lambert Beerâ€™s law (LBL), has been extensively studied [48]. LBL relates the concentration of absorbent in solution to the amount of light transmitted through the solution and absorbent. The modified method is widely used for calculating SpO_2. However, motion artifact remains a major problem when deploying SpO_2 measurement in wearable devices. Nonetheless, recent efforts have enabled accurate SpO_2 measurement from motion artifact corrupted segments [49].

As diabetes is regarded as a risk factor for cardiovascular disease, blood glucose should be continuously monitored during the patient's home recuperation, but the conventional means of invasive sampling cannot fulfill this requirement [50]. Smart contact lenses such as NovioSense can provide continuous monitoring of glucose levels through tears [51]. However, user discomfort is the biggest limitation for this type of technology given the eyes' sensitivity to foreign objects. Recent advanced techniques have enabled noninvasive continuous blood glucose measurement using only single-channel PPG, by extracting energy and spectrum features [52] or modeling PPG waveforms [53].

2.2. Wearable devices for chronic respiratory disease

Chronic respiratory disease, is increasingly threatening human health and life worldwide with the aggravation of air pollution [54,55]. Currently, it is reported that 235 million people have asthma worldwide, and more than 64 million people suffer from chronic obstructive pulmonary disease (COPD). Together, chronic respiratory disease causes about 6% of all deaths and has become the third leading cause of death worldwide [56]. Automatic early warning of lung injury related to dysfunction in ventilation has been made possible at home with the help of wearable respiratory monitoring.

As one of the most basic physiological movements, respiration can deliver significant biological information for revealing the health condition of the human body. It has been applied to identify pneumonia and sepsis, and as a marker of hypercarbia and pulmonary embolism [57].

2.3.1. Direct measurement of respiration

Many wearable devices have been developed for direct respiration monitoring based on various principles, including pressure-sensitivity, humidity-sensitivity, change of thoracic impedance, electromyography (EMG), and acceleration caused by chest movements [57,58]. Flexible pressure-sensitive materials have attracted extensive attention in the literature on wearable respiration monitoring due to their body-friendly characteristics and the ability to sense body displacement caused by respiration. They have been made into various wearable respiration sensors based on different mechanisms, such as piezoresistivity [58], piezoelectricity [59] and triboelectricity [60]. In recent years, self-powered pressure sensors have been considered to surpass the bulky design of traditional wearable breathing sensors [59], making them very suitable for long-term monitoring of chronic diseases. However, due to the uncertain response time in the mechanical deformation process, it is hard to obtain accurate timings of inhalation or exhalation via the pressure-sensitive sensor [61]. Humidity-sensitive sensors can overcome this deficiency by sensing the change of water molecules in the process of inhalation and exhalation. Therefore, humidity sensors are widely used in respiratory signal measurement with types of material, such as WS2 [62], MoS2 [63], and graphene [61].

Thoracic impedance measurement is a technique that can indirectly measure the change of lung volume caused by respiration through measuring the impedance changes between electrodes on the skin [64]. As a technology that has been used in the respiratory monitoring of severe patients or infants, thoracic impedance measurement is also widely used in wearable devices [65] thanks to their non-invasive and comfortable characteristics. The direct relationship between thoracic impedance and respiratory rate can be obtained by use of the lung model in relation to the electrode belt. Jayarathna et al. have used polymer-based stretchable resistive bands attached to a T-shirt to capture breathing information from chest expansion during sleep and light exercise (Fig. 4(a)) [66]. The commercial product Zephyr BioPatch is an easy, off-the-shelf option to measure respiration and other performance factors (as shown in Fig. 4(b)) [67]. Other studies [64,68] have shown that if the impedance sensor is sensitive enough, the cardiac signal can also be obtained at the same time.

Detecting respiratory effort using chest wall electromyography (CW-EMG) has been incorporated into sleep monitoring, and is able to classify different types of obstructive, mixed, or central apneas disorders with a high degree of accuracy [69]. The accelerometer is also an interesting alternative method to measure respiration rate given its low-cost and high reachability to patients. Previous studies have demonstrated the robustness of extracting RR signals from data collected by accelerometers under daily activity, including sitting, walking, running, and sleeping [70,71].

2.3.2. *Indirect measurement of respiration*

Breathing is physiologically connected with cardiovascular activities. Decades of research have revealed the indirect modulation of respiration in cardiac measurements such as ECG and PPG. These modulations can be divided into three types, namely baseline wander (BW), amplitude modulation (AM), and frequency modulation (FM) [57,72]. Baseline wander (BW) refers to the slow changes of signal baseline, which is usually discarded for heart analysis. AM and FM indicate the amplitude and frequency of cardiac-related peaks (QRS for ECG, systolic peaks for PPG), showing a high correlation with respiratory waveforms. While AM stems from changes in ECG recording condition (i.e., lower conductivity during inflation), FM originates from a common control of breathing and cardiac rhythms.

The standard process of acquiring breathing information comprises the extraction of respiratory signals (waveforms) and estimation of RR based on the pre-processing data after AM and FM. In this process, the critical point is to obtain robust observation of continuous breathing waveforms. Although accurate extraction can be achieved with single-mode measurement using PPG [73], the research consensus suggests that information confusion is required at both the waveform extraction and RR estimation stages, using multi-mode measurements and multiple modulations [57].

A significant advantage of using indirect measurement for respiration is that these techniques can be easily and immediately deployed into commercial devices (PPG or ECG function enabled) with only tiny firmware modifications. Therefore, PPG and ECG based respiratory monitoring are especially suitable for health monitoring of patients with chronic cardiopulmonary diseases. However, the inherent problem of low signal quality is a significant challenge in most cases. Recent efforts have introduced signal quality evaluation indexes to deal with related issues [74–76]. Orphanidou et al. have used heartbeat features and template matching to assess signal quality, automatically labeling the ECG/PPG signal as acceptable or unacceptable [77]. Such methods can significantly reduce the false alarms resulting from low quality signals. In turn, these methods can improve the battery life of wearable devices by reducing energy consumption. The development of assessment methods is necessary and has great potential in wearable healthcare devices.

2.3. *Summary of wearable techniques for chronic patient monitoring*

In addition to the various conditions outlined above, brain diseases including epilepsy and stroke are represent chronic illnesses with high morbidity and mortality across the world. Recent advanced techniques have highlighted the potential of wearable devices based on electroencephalography (EEG), EMG and inertial measurement unit (IMU) in detecting/evaluating chronic brain disease. EEG, for instance, is the gold standard for diagnosing epilepsy and can be used for automatic seizure detection. After achieving the ideal performance of seizure detection in clinical environments, an EEG collection system that can comfortably be worn in daily life is in need of development. Rosenberg et al. have designed a smart helmet for collecting continuous EEG recordings [78], and Bleichner et al. have proposed a concealed and unobtrusive ear-centered EEG acquisition device [79]. Meanwhile, numerous studies have confirmed that behind-the-ear EEG, which acquires epileptic discharges similar to scalp EEG, can be used for seizure detection [80,81]. In addition, EMG and IMU can be used for evaluation of ischemic stroke since they are user-friendly and with low-cost. Li et al. have proposed a lower-limb motion classification method for the evaluation of hemiparetic patients using IMU and EMG signals, demonstrating their potential in predicting the lower limb Brunnstrom stage for hemiparetic patients [82]. Meanwhile, Isezaki et al. have designed a sock-type wearable sensor for estimating lower leg muscle activity using distal EMG signals [83]: the sock-type EMG measurement systems can collect the target muscle electrical activity widely distributed around the shank.

To provide a uniform judgment of the techniques mentioned above and help clinical physicians and device manufacturers to select appropriate solutions for clinical use, we have summarized the wearable techniques in Table 1, with scores of convenience, costs, and robustness. We marked techniques that require no direct contact with skin and can be easily integrated into daily accessories as â€œGoodâ€ for convenience, whereas those requiring skin-contact or that are difficult to wear are marked as â€œFairâ€ or â€œPoorâ€. Costs are evaluated based on the market prices of relevant commercial devices. Some new materials-based devices/methods may also be considered as high-cost since they remain in experimental stages and are not available commercially. Robustness is judged on both inherent signal quality and noise resistance. The techniques in Table 1 are illustrated in Fig. 5 which marks the specific measuring sites for different wearable devices.

In sum, the findings of the existing literature indicate that wearable techniques can provide robust support to the long-term monitoring and diagnosis of chronic cardiovascular, respiratory and other clinical conditions.

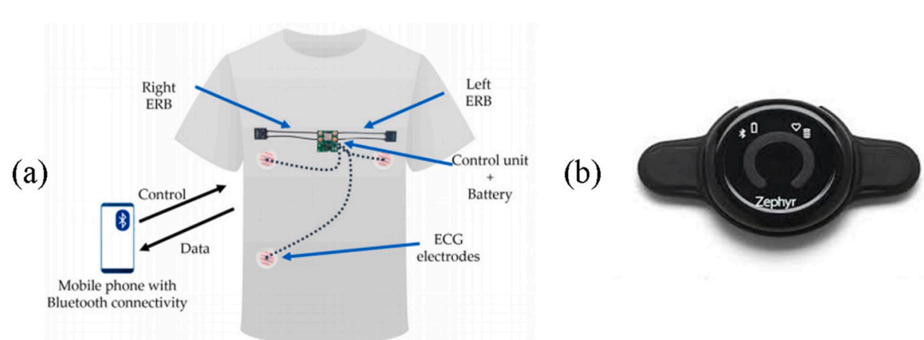

Fig. 4. Prototype for wearable respiration monitoring [66,67].

Table 1
Summary of wearable techniques used for long-term monitoring.

Aspect	Measurement Function	Techniques	Physiological Parameters	Diagnosis & Early Warning	Con-venience	Costs	Robust-ness
Cardiovascular Functions	ECG	Chest Band, Vest, Armband, Helmet, Wristband	HR (N–N), HRV; Non-invasive continuous BP	Tachycardia, Arrhythmia, AMI	Fair	Medium	Good
	PPG	Forehead Band, Ear-worn, Glove, Wrist-worn	AHR, PRV, SpO_2, Blood Glucose	AF, AMI, Mechanical Alternans	Good	Low	Poor
	BCG	Highly sensitive accelerometer	HR, Râ€“J interval	Mechanical Dysfunction, Arrhythmia	Fair	High	Fair
	PCG	Electronic stethoscope	HR, Heart Sound	Pathological Heart Sounds	Poor	Medium	Good
Respiration	Direct Measurement	Thoracic impedance	Breathing Rate, Breathing Depth, Respiratory Modes	Pneumonia, Sepsis, Hypercarbia, Pulmonary Embolism	Fair	Medium	Good
		Thermo-sensitivity, Humidity change, Triboelectricity, Piezoelectricity			Poor	Medium	Good
		CM-EMG			Fair	Medium	Fair
		Acceleration caused by chest movements			Good	Low	Poor
	Indirect Measurement	BW, AM, FM from ECG & PPG	Breathing Rate	Deterioration	Good	Medium /Low	Poor
	Respiratory Sound	Electronic stethoscope	Breathing Sound	Wheeze & Crackle	Poor	Medium	Good
Others (Epilepsy/ Stroke)	EEG	Helmet, Headset	Duration of epileptiform discharges	Seizure	Fair	Medium	Poor
	EMG	Armband, Sock-type, Wrist-worn	Motor unit Discharges, Motor unit action potential	Severity of stroke	Good	Low	Good
	IMU	Accelerometer and gyroscope	–	Severity of stroke	Good	Low	Good

3. Unobtrusive monitoring technology

Wearable devices can provide convenient health monitoring in diverse scenarios, except for those daily activities that cannot be disturbed or should be free from contact, such as sleep, study and work. In the case of cardiovascular illnesses, coronary heart disease and ischemic stroke often attack at night, for the abnormality detection of patients' states in time, so monitoring the relevant physiological signals for abnormalities at these times is essential. However, conventional clinical devices and even wearable devices may seriously interfere with patientsâ€™ sleep at night. For those relatively weak patients, especially the elderly and children, monitoring health conditions demands a more comfortable and ubiquitous solution that cannot be achieved using wearable devices alone. As a result, unobtrusive sensing technology that can be integrated into daily scenarios without user perception offers an effective response.

In the majority of studies proposed, unobtrusive monitoring techniques measure physiological signals and health parameters in a non-contact way, such as through clothes or from a certain distance. On the other hand, certain studies have measured patientsâ€™ physiological signals in contact by placing sensors on objects that may be frequently touched during specified daily activities, such as steering wheels during driving [84] or toilet seats during defecation [85]. The common feature, in contrast to wearable devices, is that they work without usersâ€™ awareness and do not interfere with the users' daily lives.

The most widely used example of unobtrusive monitoring is the remote measurement of body temperature with infrared thermometers. This technology is based on infrared thermography and has been investigated for more than sixty years [86]. It has played an essential role in the screening of severe acute respiratory syndromes (SARS) in 2003 [87,88] and COVID-19 in 2020 [89]. At present, this technology is very mature and has been implemented in many commercial products [90], supporting its immediate application to the temperature monitoring of chronic patients. Further unobtrusive monitoring technologies have rapidly developed in recent years, as shown in Fig. 6.

3.1. Unobtrusive monitoring of cardiorespiratory signals

Symptoms of cardiovascular diseases like arrhythmia or dyspnea are dangerous and should be promptly detected by unobtrusive monitoring of cardiorespiratory signals. One of the most commonly involved methods for cardiorespiratory monitoring is body surface displacement caused by heart activity or breathing. These techniques can generally be divided into the categories shown in Table 2, including radar-based, laser-based, video-motion-analysis-based, and BCG-based methods. The radar-based method obtains cardiorespiratory signals by analyzing the frequency shift between transmitted and received signals of a radar transceiver [91,92]. The laser-based method employs a laser vibrometer or laser interferometry to measure micrometer displacement of the chest wall and extract HR [93] or RR [94]. The video-motion analysis method uses an RGB or infrared camera to extract the cardiorespiratory signals

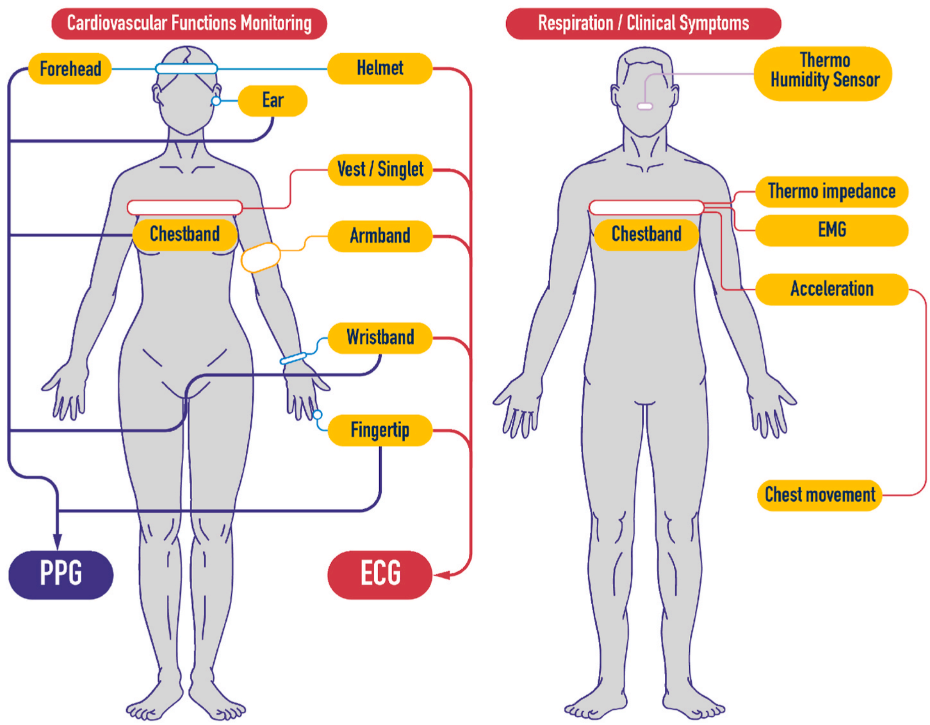

Fig. 5. Illustration of measurement sites for wearable devices used in long-term monitoring.

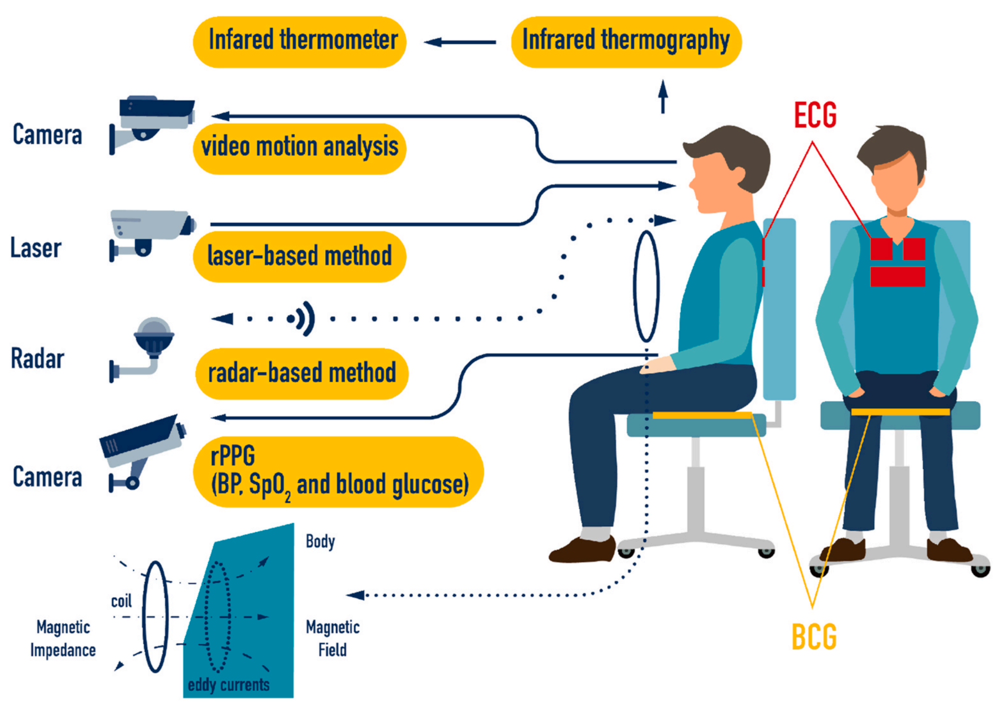

Fig. 6. An overview of the techniques involved in the use of unobtrusive monitoring technologies.

from body surface displacement quantified by optical flows [95]. These three methods are suitable for those chronic patients who do not need to move their body significantly during work or study, as the sensors can work remotely without affecting what they are doing.

BCG signal is typically measured by two types of pressure-sensitive sensors that detect resistance or charge changes caused by pressure [96]. These pressure-sensitive sensors, such as Polyvinylidene Fluoride (PVDF), may be installed into the seat cushion of a chair or the insole of a shoe [97] (Fig. 7(a)). The BCG signal could also be acquired by pneumatic sensors [98], optical fibers [99], hydraulic bed sensors [100, 101] (Fig. 7(b)) and accelerometers [102]. Since the body surface displacement caused by heart activity and breathing are simultaneous, both cardiac and respiratory signals can be extracted using displacement-based methods with a sufficient sensing resolution.

Human tissue is considered a conductor with high impedance. As mentioned above, chest impedance changes with respiratory activity, so the respiratory signal can be obtained by measuring chest impedance. Similar phenomena also occur during heartbeat activity when the blood

Table 2
Comparisons of different unobtrusive cardiorespiratory monitoring technologies.

Method	Active Energy Injection	Distance	Number of Monitored Subjects	Information	Costs
Radar-based	yes	m	>1	little	medium
Laser-based	yes	m	1	little	high
Video motion	no	m	>1	little	low
BCG	no	cm	1	medium	low
Electric impedance	yes	mm	1	little	medium
Magnetic impedance	yes	cm	1	little	medium
cECG	no	mm	1	large	low
rPPG	yes	m	>1	large	low

(a)

(b)

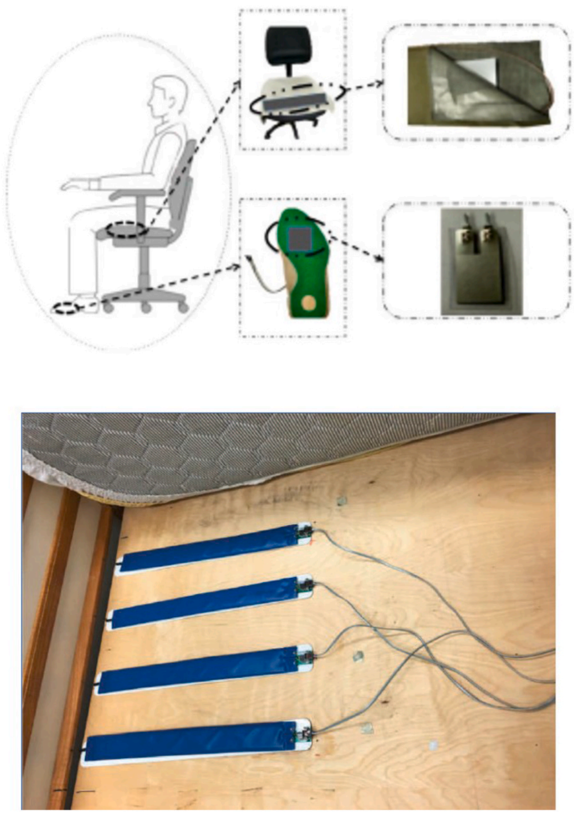

Fig. 7. Prototype for unobtrusive sensing: (a) unobtrusive BCG smart chair seat cushion [97]; (b) hydraulic bed sensor [101].

proportion and volume of the heart change. There are two ways to obtain cardiorespiratory signals by measuring chest impedance changes. The first, termed the electric impedance method, involves passing high-frequency currents into the chest using electrodes, then measuring the voltage changes caused by chest impedance variation. This method usually requires direct contact between electrodes and skin. Conversely, the feasibility of measuring to measure signals through clothes in a non-contact way has also been investigated: the gathering of heart-related information has proven more challenging, specifically due to interference from stronger noises compared to those from the chest impedance change [103,104]. The second method, the magnetic impedance method uses: a magnetic field generated from coils close to the chest to measure the induced eddy current, which is regulated by chest impedance and thus contains cardiorespiratory information [105]. Because the coils can be placed a few centimeters away from the chest, this second method is more commonly used than the first in unobtrusive monitoring. For example, by simply sewing the coils into the patient's quilt, clinicians can obtain relevant physiological signals to assess his/her health conditions. The magnetic impedance method is therefore more flexible in applications for long-term monitoring of chronic patients.

The physiological signals obtained from the aforementioned technologies can reflect heart-related information, such as HR and HRV in normal heartbeats. However, they still contain less information than clinical cardiac signals, including ECG and PPG. Fortunately, previous studies have shown that ECG and PPG can also be measured in a non-contact way.

The technology of non-contact PPG measurement, known as remote PPG (rPPG), has been studied since the mid-1990s. In contrast to the photoelectric receivers used in contact PPG measurement, in rPPG measurement, a camera is used to receive reflected photons from the skin at a distance. Videos typically captured from the face, fingers, or palms contain microvascular blood volume changes caused by the heart pumping blood. By extracting the region of interest (ROI) from each frame of the video, synthesizing the spatial information of different wavelength light, eliminating the DC component, denoising, etc., PPG signal containing heart rate information can be obtained [106]. In previous studies, an active light source with one or a combination of blue, green, near-infrared and red light was selected to provide photons and a scientific charge-coupled device was needed [107], restricting the realization and application of this technology in daily life. With the development of related hardware and algorithms, rPPG measurement can be realized more conveniently, even using consumer cameras or webcams [108] and ambient light sources [109,110]. However, many studies have shown that the accuracy of heart information estimation to be affected by the camera frame rate [111,112], image resolution [113], as well as video compression during storage [114,115]. Therefore, using consumer cameras to obtain stable and high-quality PPG signals still has some challenges, especially the low frame rate. Despite their high level of convenience, some of the above unobtrusive monitoring techniques are therefore not the first option in particular scenarios.

The technology of non-contact ECG measurement, termed capacitive coupled ECG (cECG), has been studied since the mid-1990s. When measuring ECG through clothes, the electrode is separated from the skin, leading to an extremely large skin-electrode impedance, which further results in the high susceptibility of the measured signal to diverse interferences [116]. Designing a buffer with high input impedance close to the electrode makes it possible to measure ECG through clothes, with the option of a right leg drive (RLD) electrode to feed the common mode signal back to the body. In previous studies, cECG systems have already been embedded into various objects in daily life scenarios, such as beds [117,118], chairs [116], driver's seats [119], toilet seats [120] and bathtubs [121]. The electrode materials used in these systems include conductive fabric, copper foil tape, and flexible printed circuit [116]. Together, these studies indicate that cardiorespiratory signals may be effectively measured in a range of everyday domestic settings, thereby allowing the ongoing monitoring of various chronic health conditions.

In contrast with photoelectric receivers in contact PPG measurement, a camera that can shoot the region of interest from a distance is used to receive reflected photons using both ambient light and active light. The active light can be further divided into monochromatic light and polychromatic light, with one or a combination of blue, green, near-infrared and red light [122]. In previous studies, scientific charge-coupled device (CCD) camera system with high signal to noise ratio (SNR), quantum efficiency and frame rate has been used [107]. Consumer CCD cameras

[109] were also applied in these studies. Moreover, use of smartphone camera applications have also been studied in recent years [110]. For example, when applied to sleep monitoring of chronic patients, cECG and BCG measurement systems with strip-shaped sensors placed across the bed are preferred (as shown in Fig. 8), given that patients may repeatedly turn over or arbitrarily move their bodies in unconstrained sleep. However, such techniques can still be promisingly employed in numerous scenarios without obvious movement, such as working, eating, and so on.

All these cardiorespiratory monitoring technologies have different characteristics, as shown in Table 2. Unlike other techniques, where the distance between sensor and body is at the centimeter or even millimeter scale, radar-, laser- and camera-based technologies can work at sensor-to-body distances of up to 1 m. Additionally, the ECG and PPG signals measured by cECG or rPPG techniques contain the most salient physiological information because they are the most similar to the clinical cardiac signals. A comparison of a variety of characteristics of different techniques can be found in Bruser et al. [104].

3.2. Physiological parameter extraction

As mentioned in section II, physiological signals including BP, SpO_2 and blood glucose can reflect the condition of patients with chronic cardiovascular disease, respiratory disease or diabetes and should be continuously measured. For monitoring in special scenarios, the above unobtrusive techniques can be used to measure these physiological parameters indirectly.

Similar to BP measurement in wearable monitoring (which can be derived from PPG signals), non-contact BP monitoring can also be achieved using information from rPPG signals. For example, previous studies have investigated the correlation between BP and PTT calculated using rPPG signals from two different body parts, such as wrist and ankle [123,124]. However, the measurement of PPT between two body parts requires a relatively high sampling rate, which may be a challenge for consumer cameras with low frame rates [106]. Nevertheless, PTT obtained from rPPG signals and other wave features may then be combined to estimate BP. The advancement of unobtrusive monitoring of BP has been further promoted due to two factors. On the one hand, stable ambient light is made available for the light source to acquire rPPG signals [125]. On the other hand, BP can be estimated using rPPG signals obtained from a specific body part [126]. In a recent study by Luo et al. in 2019 [110], PPG signals from 1328 normotensive adults were captured using a smartphone camera. A multilayer perceptron machine

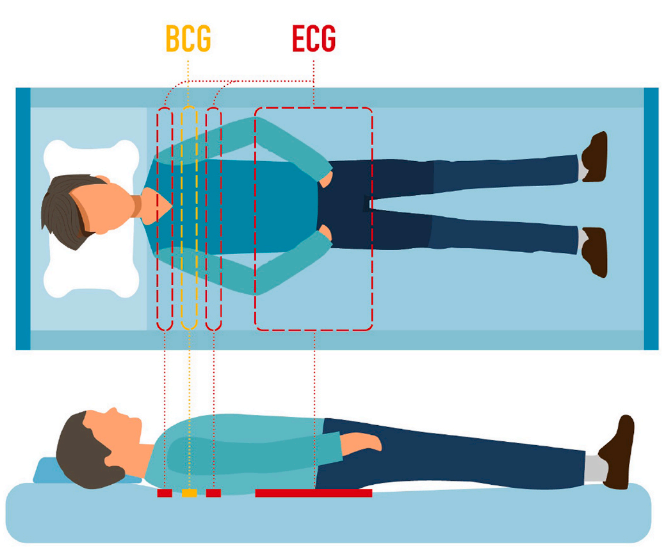

Fig. 8. Unobtrusive monitoring techniques for cardiorespiratory signal monitoring overnight.

learning algorithm was then employed to train a computational model for BP estimation. The results showed that the prediction errors of systolic pressure, diastolic pressure and pulse pressure were 0.39% Â± 7.30 mmHg, âˆ'0.20 Â± 6.00 mmHg and 0.52 Â± 6.42 mmHg, respectively.

Non-contact BP measurement methods based on other principles have also been proposed. Ohata et al. [127] have used a Doppler radar to measure cardiac signals; BP can then be estimated from the systole duration of each heartbeat. Sakajiri et al. [128] have integrated fabric-sheet electrodes into the design of a bed to measure cECG and BCG signals in a non-contact way: BP estimation is calculated using the pulse beat arrival time. A hydraulic bed sensor system for BCG measurement [101] has also been used to estimate relative systolic BP by extracting features based on the strength and morphology of the bed sensor BCG pulses. However, only the correlation between BP and extracted features was analyzed in these studies. In Ref. [129], an electric circuit model was constructed to describe the vascular structure of an entire face by thermo-hue hemodynamic analysis, which was then used to estimate BP. Despite the performance improvement achieved in subsequent studies [130,131], the estimation error of BP is still too large to meet the application requirements under international accuracy standards.

Remote PPG is also the most commonly used method for unobtrusive SpO_2 monitoring. At least two wavelengths of light are used to obtain the rPPG signals. SpO_2 is then calculated by combining multi-wavelength rPPG signals. Typical wavelength combination is red and near-infrared wavelengths. The conventional signal combination method is the â€œratio-of-ratiosâ€ (RRs) method based on LBL [132]. In previous studies, one research direction has been to replace the RRs method with other methods, such as combining the obtained PPG signals to construct a pulse signal set with the best signal quality [133,134]. Further studies have also attempted to replace the combination of red and near-infrared light with a combination of visible lights, such as red and blue light [135], or red and green light [122], with the intention of remotely monitoring SpO_2 using consumer cameras, such as those on smartphones. These easily accessible cameras can contribute to the real-world applications of unobtrusive SpO_2 monitoring in the very near future. Significant challenges remain, however, especially the low frame rate in consumer-grade cameras and the impact of video compression during storage.

In addition, previous studies have also used smartphone cameras to monitor blood glucose. Dantu et al. [136,137] have used an HTC One X Android phone camera to detect the transmitted photons on finger, from which PPG signals with two wavelengths were obtained. However, only a near-linear correlation between blood glucose and the ratio of PPG signals with two wavelengths was obtained. Zhang et al. [138] have used a smartphone camera with a frame rate of 28fps to acquire PPG data on the left index finger and then employed a machine learning classifier to estimate blood glucose levels.

In general, there have been two major developments in past studies on unobtrusive monitoring. On the one hand, the use of consumer-grade rather than scientific-grade sensors have made remote monitoring easier to implement in daily life. On the other hand, the proximity-sensing sensors have been successfully integrated into a variety of daily necessities, so that patients can imperceptibly monitor their chronic health conditions any given scenario, including work, sleep, driving, home life, etc. Therefore, these technologically mature techniques can support extensive long-term monitoring of chronic diseases.

4. Early warning and dysfunction detection

Monitoring physiological parameters continuously is not the full story of wearable device evaluation. State-of-the-art techniques have enabled early warning of health condition deterioration and 24-h real-time detection of dysfunction, which can provide timely information for decision-making in diagnosis and treatment.

Although automated arrhythmia detection from single-lead ECG has been extensively studied, its state-of-the-art algorithms usually rely on high-accuracy QRS and PT wave detection [139], which may not work effectively if used directly on data collected from wearable devices, considering the relatively poor signal quality and limited computational resources. End-to-end deep learning-based methods have been developed to solve this problem. Moreover, these approaches require no ECG segmentation, or only QRS detection (a simple task as mentioned earlier), and are more robust to ECG noise [140,141]. Deep learning-based methods have also been carefully optimized and can be deployed into mainstream wearable devices for real-time heartbeats screening [142,143].

Myocardial infarction (MI), is another common cardiovascular disease, is mostly characterized by ECG via ST changes, with the exception of non-ST-elevation myocardial infarction (NSTEMI). The automatic detection and localization of MI using 12-lead ECG have been extensively studied using machine learning algorithms [144]. However, when wearable devices are used as data acquisition equipment, several modifications are required to account for the limited numbers of leads and the relatively low signal quality. Research has also been conducted on wearable-compatible algorithms for acute MI (AMI) detection based on two pairs of electrodes and has achieved high sensitivity [145].

PPG has also shown potential in the diagnosis of cardiac dysfunctions. Atrial fibrillation (AF) detection on in-hospital patients using wrist-worn PPG has been illustrated in Ref. [146], showing impressively high accuracy within- and cross-subject. Another study has demonstrated that a deep neural network applied to wrist-worn PPG can passively detect AF through a large population with commercial devices [147]. PPG may also contribute to the automated screening of MI [148] and non-invasive detection of mechanical alternans of blood pressure [149].

Furthermore, several studies have proven the effectiveness of using AI techniques to identify pathological heart sounds [150]. We believe that the techniques above stand to provide substantial assistance in the monitoring and treatment of chronic cardiovascular diseases and to benefit patients at home who may experience a deterioration in cardiovascular function.

Respiratory sound provides another way to monitor breathing conditions and can be easily measured by commercial electronic stethoscopes attached to the chest. Abnormal respiratory sounds mainly include attenuated sounds as well as increased, abnormal sounds. A trained physician can easily recognize pathological breathing from respiratory sounds, while wearable techniques have enabled real-time ambulatory detection of abnormal breathing events. Respiratory sounds collected by wearable sensors have been used for wheeze and crackle analysis by applying a hybrid CNN-RNN framework on the Mel spectrogram [65]. Apnea events, another common abnormal respiratory event, can be detected using the sound-level sensor on a smartphone [151]. Compressive sensing is also involved in this issue to meet the real-time and low-consumption requirements of wearable devices [152]. These previous studies indicate the vast potential of wearable respiratory sound monitoring for patients with chronic respiratory disease.

5. Conclusion and future directions

This review of existing studies on wearable devices and unobtrusive sensing technologies provides an array of possible applicable techniques may can be immediately used for chronic disease management. Despite the evident advancements, the tremendous true potential of technology-enabled healthcare management for patients and ageing people remains to be tapped.

Although wearable devices have become a topic of widespread discussion, frustratingly few wearable techniques are in practical circulation. Certain limitations restrict unobtrusive technologies from expansion into more practical contexts. Signal collection is not as robust as those from conventional medical equipment, for example. This may be attributed to the wearable setups (such as textile electrodes), which are primarily designed for long-term wear and thus have to compromise on signal quality.

Unobtrusive sensing has shown great potential across many clinical scenarios. However, most technologies still cannot precisely monitor physiological signals over long periods. For example, remote monitoring technologies including rPPG, radar-based, laser-based and video motion methods cannot feasibly be used for sleep monitoring overnight at present due to activities that may inadvertently terminate monitoring during sleep, such as moving quilts or turning the body over. Therefore, a development direction for remote monitoring is to solve the inefficacy problem under the normal movement of daily activities. Moreover, considering that the signal measured by each individual technique is less reliable and of poor quality, sensor fusion is needed. Although smart mattresses that use a single technique (e.g., cECG or BCG acquisition) can achieve long-term sleep monitoring overnight, only limited health parameters can be measured, restricting their value to the health monitoring of chronic patients. By integrating cECG and BCG, or embedding non-contact PPG measurement techniques into the smart mattress, a broader range of health parameters, such as BP, SpO_2 and blood glucose, could potentially be derived from the acquired signals in an indirect way.

In addition, the majority of wearable or unobtrusive technologies reviewed here can achieve disease detection and analyze the pathological mechanism automatically, thus reducing the heavy workload of medical staff. However, early warning of patient state deterioration is a more challenging prospect; if achieved, it could provide both patients and medical staff with sufficient time to avoid risks. For example, during the COVID-19 pandemic, early warning algorithms via respiratory disease symptom monitoring can remind high-risk populations of infection risks, and taking advance precautions would contribute to limiting the widespread cross-infection of COVID-19.

More broadly, rather than using wearable and unobtrusive technologies separately, effective ways to integrate the two techniques in various application scenarios should be investigated. Another practical concern is the fact that the power consumption and battery size of wearable devices are largely limited by the requirements of hardware miniaturization and power supply safety, which greatly affect the lasting duration of health monitoring. Therefore, reducing energy consumption to ensure the long-term use of devices warrants further investigation. The hardware design of low-power consumption architecture and energy-efficient algorithms are two approaches to achieve high energy savings [153–155]. The former typically aims to reduce signal resolution while at the same time meeting the minimal requirements of application scenarios. For example, low-power consumption can be achieved by reducing the burden of data transmission with low sampling rate and AD resolution. The latter approach aims to achieve low power consumption by reducing model size or algorithm complexity without greatly reducing the performance of healthcare monitoring.

Existing solutions to implement new and improved algorithms rely greatly on cloud computing, which means the data collected from terminals have to be fully uploaded via telecommunication. As a whole, the data uploading procedure may lead to privacy concerns, and users may worry that their data is disclosed by third parties. Most devices based on the Internet of Things (IoT) may also be susceptible to various threats and attacks, such as malicious data modification, impersonation attack, and eavesdropping [156]. Similarly, rising interest in blockchain technology, which theoretically allows for the construction of a digital database among different users without sacrificing privacy [157], is still mired in security fears. Possible solutions including machine-learning ASIC, separating algorithms and cloud-based parts, which can facilitate feature extractions from raw data and inform decision-making in an appropriate way.

Finally, most studies on remote monitoring devices have focused on the function implementation of signal acquisition and diagnosis of the disease. However, the research on improving practicalities of remote monitoring devices and promoting user experience remains limited. In particular, studies from the perspective of user interface and interaction design can greatly improve convenience, so as to foster patients' acceptance, adoption and sustained engagement with these remote monitoring techniques [158]. For example, without professional instruction, the practical everyday use of wearable or unobtrusive monitoring devices is typically more challenging than that of conventional medical equipment, causing patients to question monitoring performance. Taking patientsâ€™ habits and behaviors into consideration and testing new devices across wider and more heterogeneous groups and in more complex scenarios are two effective methods to improve human computer interaction and user experience [159]. Such studies given greater emphasis to optimize wearable and unobtrusive monitoring devices for practical use.

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