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Sensing beyond itself: Multi-functional use of ubiquitous signals towards wearable applications

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ABSTRACT

Wearable technologies provide a non-invasive way to monitor user's activity, identity, and health in real-time, which have attracted tremendous interests from both academia and industry. Due to constraints in form factor and power consumption, the sensing capabilities and functionalities of the wearables are usually limited by the available sensors. In the past decade, researchers have committed to realizing the sensing capability of multiple sensors via the signal from one sensor, which expanded the functionalities and sensing domains of traditional sensors. For the first time, we defined such sensing approach as "**cross-sensing**" and provided a comprehensive review on the cross-sensing towards wearable applications (*i.e.*, human-machine interface, health services, and security). Specifically, this paper summarized the applied signal processing and machine learning algorithms, and discussed how cross-sensing would affect the development and innovation trends of wearable electronics.

1. Introduction

Wearable electronics provide a highly flexible real-time sensing platform for user-centered services [1–4] such as human-machine interface (HMI) [5–9], health monitoring [10–15], security credentials [16–19], and many other Internet of things (IoT) applications [20–22]. Progress in mechanics, materials, sensing technologies, and data science drives the research thrusts in wearable electronics in academia. The market has also witnessed the enormous commercial value of smart wearable products. According to the up-to-date forecast from Statista, the global market volume of smart wearable products is projected to reach USD $17.85 billion in 2024 [23].

Compactness and functionalities are two critical considerations for the design of wearable devices [24]. A comfortable wearing experience relies mainly on the small size, lightweight, and soft mechanics of the device. However, the demand for the tiny form factor and battery-powered feature poses many challenges. For example, the encapsulated sensors need room to accommodate bulky batteries for adequate power supply; the low-power design for longer operation time bounds the implementation of computing and memory-consuming applications.

To address the above challenges, many researchers attempt to use the signal from one sensor to realize the sensing capability of multiple types of sensors. We define this sensing paradigm as "**cross-sensing**", which exploits extra sensing capabilities beyond the sensor's original designed usage and expands the perceptional dimensions of sensors. (i.e., sensing beyond itself) In the past decade, the advancement of many technologies made cross-sensing possible. For instance, microelectromechanical systems (MEMS) technology [25] shrank the physical size of an individual sensor and integrated multiple sensing components into a single device to create more compact hardware; heterogeneous computing [26–29] improved computing and signal processing efficiency by introducing multiple co-processors to the wearables' system on chip (SoC); compressive machine learning [30–33] made the deployment of complex machine learning models on the wearables possible.

Our comprehensive survey summarizes the innovation on three categories of wearables' usages frequently appeared within the scope of cross-sensing (Fig. 1). The first category includes entertainment and HMI realized by devices designed for communication, sound recording. In the second category, RF signal, acoustic signal, visual signal, and motion signal are utilized for health and

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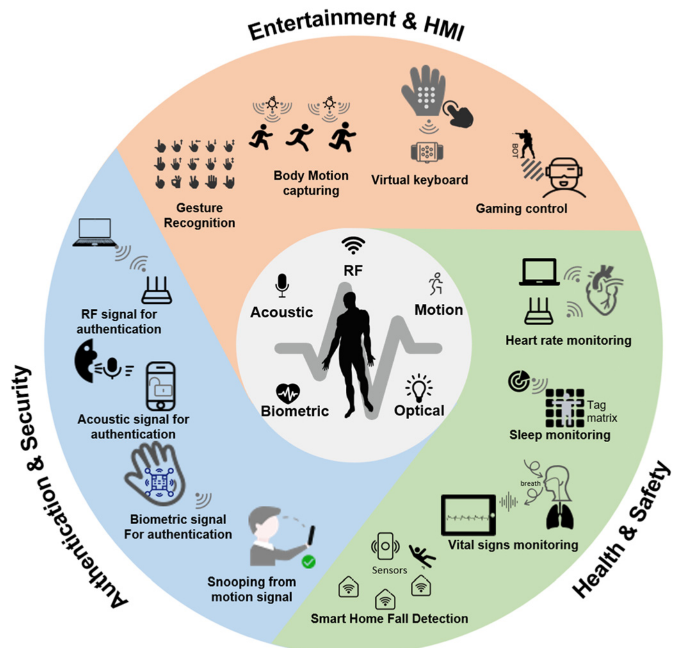

Fig. 1. The schematic diagram illustrates three major wearable application categories realized in cross-sensing.

safety applications such as non-intrusive vital sign monitoring, fall detection, sleep monitoring, and mental state detection. The third category is related to security applications and issues, where cross-sensing not only enables continuous and senseless user authentication but also poses the risk of eavesdropping via wearables.

The rest of this article is organized as follows: Section 2 introduces the entertainment and HMI related application. Section 3 reviews the health and safety services conducted by non-biomedical devices. Section 4 surveys the authentication and security applications. Section 5 presents the summarization and our perspectives on the future development of wearables. For better readability, Table 1 summarizes the mentioned abbreviation of signal processing and machine learning algorithms.

2. Entertainment and HMI

HMI is one of the most important parts of wearables. This section reviews how cross-sensing utilizes signals in wireless communication systems and acoustic systems to provide interfaces for various entertainment applications and facilitate diversified interaction styles.

2.1. Contact-free body movement tracking

Human body movement tracking in wearables allows users to experience immersive augmented reality (AR) and virtual reality (VR), play *Xbox Kinect* [34] games, and initiate the smart home's IoT devices. Although imaging-based systems (e.g., Intel RealSense [35], Xbox Kinect [34], Leap Motion[36]) are available in the market. However, they raised potential privacy issues, and meanwhile, the performance is sensitive to occlusion and illumination conditions. Moreover, they do not make the utmost of existing infrastructures. The wireless communication signals (including radio frequency (RF) communication signal and visible light communication (VLC) signal) fulfill these applications in a contact-free manner, which is more practical and attractive than having users wear or carry additional devices. Fig. 2 summarized the cross-sensing enabled contact-free body movement tracking.

Table 1
Abbreviations of signal processing and machine learning algorithms in this article

Abbreviations	Definitions
ACF	Auto-Correlation Function
ADMM	Alternating Direction Method of Multipliers
ANN	Artificial Neural Network
CFCC	Cochlear Filter Cepstral Coefficients
CWT	Continuous Wavelet Transform
DAM	Doppler Angle of arrival Mapping
DBN	Deep Belief Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DNN	Deep Neural Networks
DTW	Dynamic Time Warping
DW-PC	Differentiated Window-based Phase Change calculation
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
FWPT	Fuzzy Wavelet Packet Transform
GAN	Generative Adversarial Network
GFCC	Gammatone Frequency Cepstral Coefficients
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
HT	Hilbert Transform
ICA	Independent Component Analysis
k-NN	k-Nearest Neighbors
LSTM network	Long Short-Term Memory network
MFCC	Mel Frequency Cepstral Coefficients
MST	Minimum Spanning Tree
PCA	Principal Components Analysis
RNN	Recurrent Neural Network
root-MUSIC	root-MUltiple SIgnal Classification
RPN	Region Proposal Network
SOFT	Sliding-window Overlap Fourier Transform
SSWPT	Synchro Squeezed Wavelet Packet Transform
SVD	Singular Value Decomposition
SVDD	Support Vector Domain Description
SVM	Support Vector Machine
TPCC	Teager Phase Cepstrum Coefficients
VMD	Variational Mode Decomposition

2.1.1. Via RF signal

RF signals are the electromagnetic (EM) waves modulated with data. Apart from data transmission, the ubiquitous RF signals can be leveraged for body movement tracking.

In 2014, Adib et al. introduced a millimeter-wave (mmWave) RF signal-enabled 3D body tracking system, *WiTrack* [37], as shown in Fig. 2(a). The system first utilized frequency modulated carrier waves (FMCW) to estimate the time spent on the signal reflected from the human body. The FMCW radio system mapped the time of flight (ToF) of EM wave to carrier frequency shifts, which drastically reduced the complexity of implementing ToF estimation *WiTrack* introduced a background subtraction scheme to eliminate the interference of static background and extract the three-dimensional (3D) position of a single user with decimeter-level accuracy. As an upgraded version, *WiTrack2*.0 [39] achieved localization of multiple users with two more transmit antennas. The successive silhouette cancellation algorithm proposed in *WiTrack2*.0 overcame the near-far problem; specifically, the EM wave reflected from the nearby user may overlap the reflection of users in the distance. In order to enrich body movement details, Zhao et al. proposed *RF-Pose3D* [38], a mmWave-based 3D human skeletons reconstruction system. Two components of the *RF-Pose3D* system are shown in Fig. 2 (b). The pose labels generated by the camera system are used to train a two-stage neural network model that reconstructs a multi-person 3D skeleton from the multi-antenna FMCW mmWave signal. In the first stage, RPN was used to crop the regions with a single user's RF signal reflection. Then the second stage adopted CNN to classify the user's body key points (e.g., head, neck, knee) to 3D space voxels.

As the most popular wireless communication protocol in smart devices, Wi-Fi-based human position tracking is more conve-

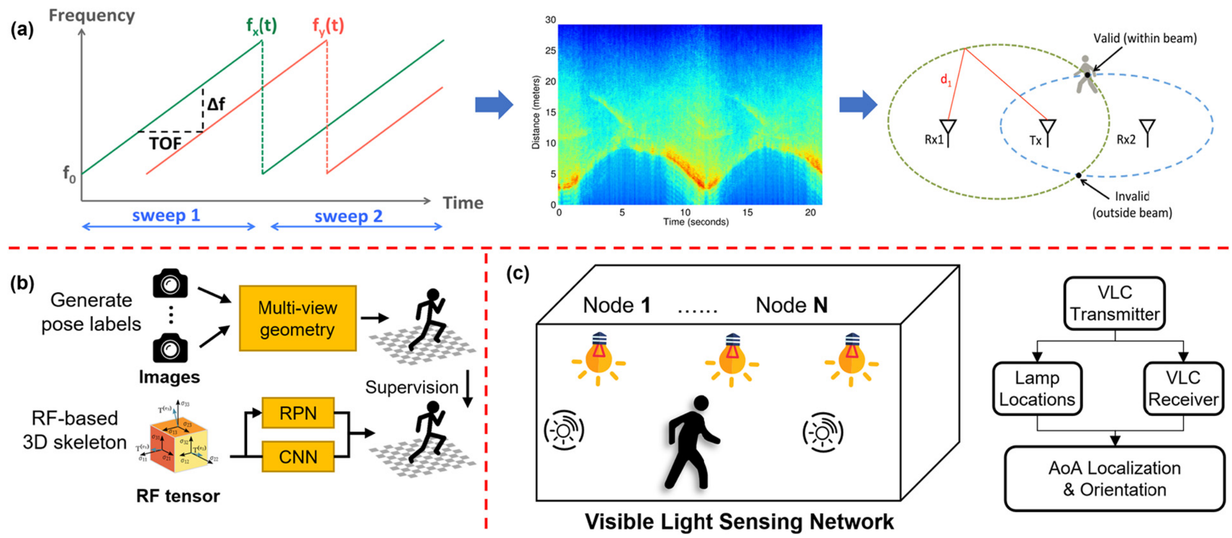

Fig. 2. Cross-sensing leverages wireless communication signals for contact-free human movement tracking. (a) Flowchart of the *WiTrack* 3D human tracking system with three main steps, frequency modulated carrier waves (FMCW) operation for ToF estimation, static background subtraction, and localization. Reproduced with permission [37]. Copyright 2015, The Advanced Computing Systems Organization. (b) *RF-Pose3D* uses RF signal to reconstruct the 3D human movement skeleton [38]. (c) Schematic illustration of using VLC nodes to obtain the user's position by detecting the projected shadow.

nient for deployment than the mmWave-based solutions. In 2017, Qian et al. proposed *Widar* [40], the first system that achieved decimeter-level passive tracking via commodity Wi-Fi. The *Widar* system analyzed the variation of channel state information (CSI) power segments of different orthogonal frequency division multiplexing (OFDM) subcarriers caused by human movement to estimate the moving velocity and location of the person. To make the system more compact, Widar2.0 [41] only used a single receiver to overhear the packet and calculate ToF, angle of arrival (AoA), and Doppler frequency shift (DFS) of the reflection for location estimation. In 2020, Wu et al. adopted commodity off-the-shelf (COTS) WiGig (IEEE 802.11ad high-speed Wi-Fi protocol) for passively multi-users tracking [42]. By digital beamforming on the antenna array of the WiGig device, it achieved a high spatial resolution of 4.26 cm with a working range of 4 m.

2.1.2. Via visible light signal

VLC is a rapidly emerging optical wireless communication technology that provides a higher data rate than traditional RF communications [43–45]. The wavelength of visible light is within a sub-micron meter range, making accurate indoor positioning possible with the off-the-rack VLC systems as depicted in Fig. 2(c).

LiSense [46] demonstrated that the visible light spectrum could be used for both communication and fine-grained human sensing. The VLC system adopted by *LiSense* is built by five light-emitting-diodes (LEDs) installed on the ceiling and 324 photodiodes (PDs) embedded on a 3 m×3 m testbed. The shadow projected from each light source can be differentiated by frequency modulation of light intensity for each LED. Li et al. moved the PDs to the ceiling for more practical implementation and locating the moving human skeleton by recovering the shadow projected on the ceiling [47]. Ibrahim et al. further integrated LEDs and PDs into one lamp [48], each LED lamp's light can be identified via a time-division multiple access (TDMA)-like scheme. The *PIXEL* [49] system proposed a polarization-based modulation to enable low pulse rates VLC for real-time positioning and an AoA-based algorithm to determine the user's location and orientation. Visible light-based positioning can also be achieved without modifying the existing lighting infrastructures [50]. Konings et al. installed PDs on the wall to realize centimeter-level indoor human positioning [51]. The proposed *FieldLight* algorithm applied the artificial potential field to achieve positioning without labeled training data for calibration.

2.2. Pervasive human-machine-interface

Wearable electronics such as smartwatches and smart wristbands provide handy computation platforms. However, compared with traditional computers, tablets, or even smartphones, the small screen limits the richness of the input forms and makes text input cumbersome. Beyond their original function, the cross-sensing enables RF signal and acoustic signal to adopt multiform HMI and expand the operation interface of wearables, as depicted in Fig. 3.

2.2.1. Via RF signal

People often use hand gestures to express their intentions. Cross-sensing enables pervasive RF signals for recognizing user's gestures wirelessly and provides an intuitive HMI experience. In 2016, Lien et al. presented *Soli*, a mmWave radar-based HMI architecture (Fig. 3(a)) [52]. *Soli* adopted a customized solid-state radar chip to transmit RF signal and receive reflections from each finger. Then the received raw signal is transformed into a range-Doppler image, range profile, and micro-Doppler profile for gesture classification. *Soli* pushed the hand motion sensing to impressive mm-level accuracy; however, the specialized mmWave chip had not been integrated into most commodity devices. Fortunately, pervasive Wi-Fi signal provided more favorable solutions for gesture recognition [56]. To improve the generalization ability of Wi-Fi-based hand gesture recognition in different domains (e.g., environments, locations, orientations), Zheng et al. extracted domain-independent hand gesture features (body-coordinate velocity profile (BVP)) from the domain-dependent signal [57]. Although hand gestures are auxiliary for healthy people to interact and communicate with others, they play a more significant role in people facing speech and hearing adversities. *SignFi* [58] demonstrated a Wi-Fi-based sign language interpreter capable of recognizing 276 sign gestures with 94.81% accuracy.

Cross-sensing also enables RF signal for convenient text input and graph plotting. In 2020, Han et al. proposed *AirDraw* [59], which used three devices to achieve hand movement tracking. The robust signal calibration algorithm *AirDraw* reduced median error to lower than 2.2 cm within a tracking range of 1.5 m.

2.2.2. Via acoustic signal

The acoustic signal provides the opportunity of expanding the interaction interface by mapping a virtual keypad for numerical

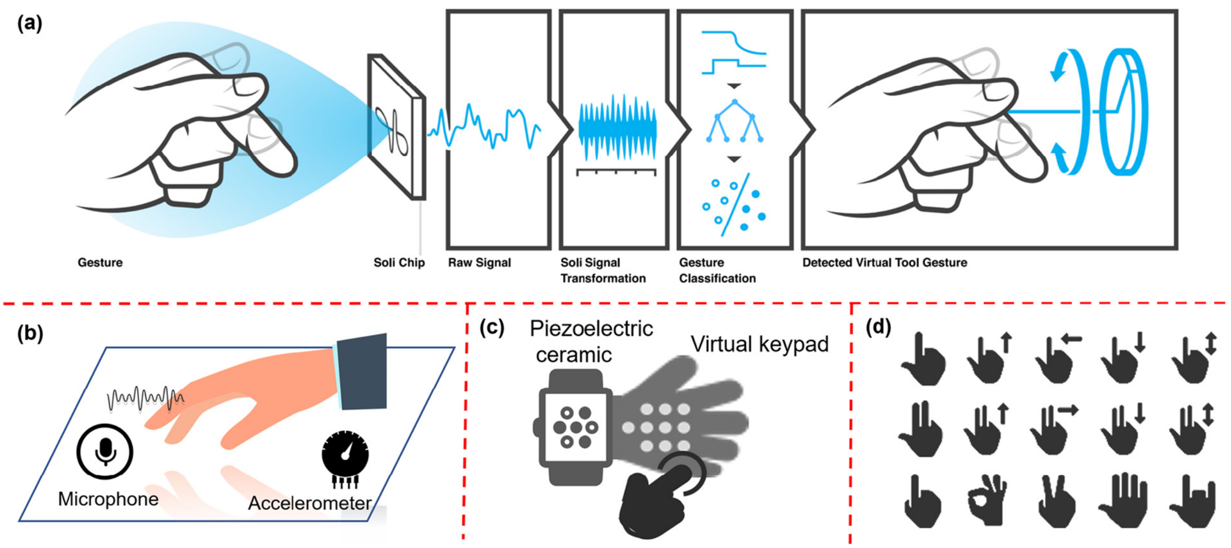

Fig. 3. Gesture recognition and virtual input via RF and acoustic signal. (a) The flow chart of *Soli*, the first mmWave radar system for gesture interaction. Reproduced with permission [52]. Copyright 2016, Association for Computing Machinery. (b) Wearable accelerometers and microphones can obtain the location of taps on general surfaces [53]. (c) *ViType* enabled on-hand typing at arbitrary positions [54]. (d) *UltraGesture* leveraged acoustics signal to recognize 12 gestures for smart device control [55].

input and text input. Early in 2016, Zhang et al. fused acoustic and motion signals from commodity smartwatch's microphone and inertial measurement unit (IMU) [60] to detect the on-skin virtual keyboard tapping. Recently, Gong et al. expanded such taping recognition to more general surfaces, such as wood, plastic, steel, and glass, as illustrated in Fig. 3(b) [53]. *ViType* [54] used a single piezoelectric ceramic transducer to capture the vibration of tapping on opisthenar (Fig. 3(c)). Based on the uniqueness of acoustic propagation in different individuals, *ViType* allows users to define their desired touch region by a few minutes of training. Apart from tapping, handwriting is also a popular way for text input. *Sound Write* [61] leveraged amplitude spectrum density features to identify the writing stroke on the wood table, *WordRecorder* [62] investigated time-frequency features, *Ubiquitous writer* [63] extracted the MFCC features to infer letters written on paper from the nib swipe sound. Commodity wearable mobile devices can actively send and receive acoustic signal to recognize handwritten digits and letters in the air [64–68]. Specifically, *AcouDigits* [64] and *EchoWrite* [65] extracted Doppler profiles corresponding to different in-air finger writing strokes, and then the DTW was adopted to match the template. *VPad* [68] analyzed energy features and Doppler shifts of acoustic signals to accurately track the user's fingertip for "touch screen" function.

Using the phase change of the 17 kHz sound wave, *FingerSound* [69] achieved single-finger gesture tracking. Collecting passive acoustic signals from finger gestures, *IPand* [70] proposed a novel thumb gesture recognition scheme. Luo et al. fused MFCC and CFCC to provide accurate and robust recognition for gestures performed on wood tables [71]. *UltraGesture* [55] analyzed channel impulse response (CIR) from the commercial speakers and microphones, providing 7 mm resolution, and showed a 97% accuracy for recognizing 12 gestures depicted in Fig. 3(d).

The pervasively available speakers and microphones make acoustic signal-based motion tracking an easy-to-implement approach for VR/AR experience and game controls [72–76]. Conventional acoustic finger movement tracking is achieved by actively playing inaudible sound waves and applying frequency analysis to the reflected waves, which introduced high computational overhead and delay. Inspired by vernier's working principle, Liu et al. proposed a novel differentiated sliding-window-based phase change calculation scheme to accurately and efficiently track the motion of acoustic sources [77]. *EarphoneTrack* [78] adopted wired and wireless earphones as acoustic sources and provided a highly flexible acoustic HMI interface. Comprehensive experiments demonstrated that *EarphoneTrack* only undergoes approximately five milliseconds of end-to-end system latency, which enabled a smooth user experience even in action games.

3. Health and safety

Wearables' proximity to the human body is their advantage of hosting health and safety services. Conventional biometric monitoring function in wearables is addressed by biometric sensors like electrocardiogram (ECG), electromyography (EMG), and photoplethysmography (PPG). However, the adoption of multiple biometric sensors in wearables aggravated the battery lifetime shortage and raised the cost significantly. Numerous studies have reported health and safety-related services delivered in cross-sensing, where devices other than wearable biometric sensors can facilitate vital sign monitoring, smart home health services, and mental states monitoring.

3.1. Vital sign monitoring

Vital sign monitoring is a typical wearable application, giving users a better understanding of their health condition and triggering medical assistance upon emergencies. As shown in Fig. 4, RF signal, acoustic signal, and computer vision technologies exhibit their potential for vital sign monitoring.

3.1.1. Via RF signal

Compared with contact-sensor based approaches, many benefits can be seen from RF-based vital sign monitoring. First, continuous monitoring can be made without users wearing any assessor. Moreover, contactless monitoring can lower infection risk, especially in medical facilities.

There have been some studies showing the capabilities of RF signals for monitoring various physiological parameters. In 2018, Wang et al. proposed *RF-ECG* [81], which achieved a comparable inter-beat-interval measurement accuracy to traditional wired methods in wireless and battery-free design. *RF-ECG* attached low-cost RFID tags on the chest area in the cloth to assess the heart rate variability (HRV), a useful diagnostic clue for cardiac health evaluation.

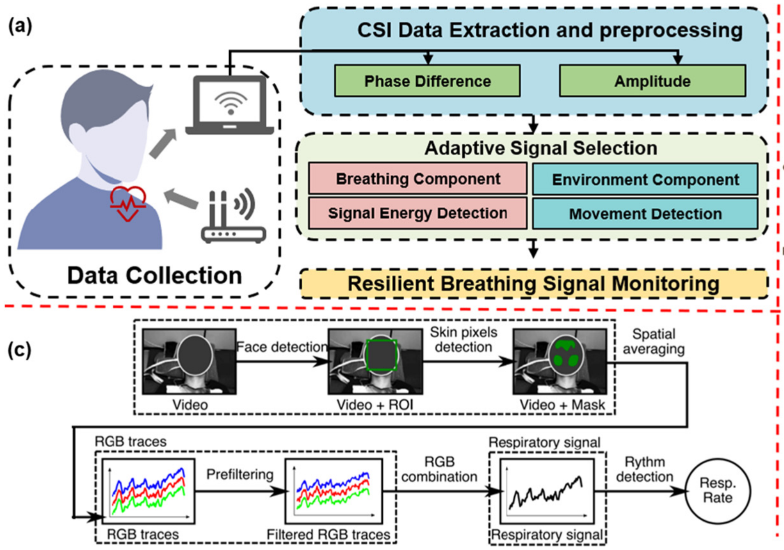

Fig. 4. RF, acoustic and visual signal enabled vital signs monitoring. (a) The pipeline of commodity 5 GHz Wi-Fi-based respiration rate monitoring system. (b) Exploded schematic illustration of a skin-mounted soft electronic device that can monitor multiple biometrics. Reproduced with permission [79]. Copyright 2020, Springer Nature. (c) The processing pipeline of the vision-based remote photoplethysmography Reproduced with permission [80]. © 2021 Elsevier

Apart from RFID, ubiquitous Wi-Fi-based vital sign monitoring also attracted great interest. Fig. 4(a) demonstrates the pipeline of *ResBeat* [82], which utilized both amplitude and phase difference of CSI data from commodity 5 GHz Wi-Fi system to estimate respiratory rate (RR) and analyze the anomalies in breathing. However, *ResBeat* only supports breath monitoring for a single user. In 2020, Gao et al. used the DAM to make the Wi-Fi-based respiration monitoring available for three people in the same room [83]. Since CSI represents fine-grained channel information, *PhaseBeat* [84] adopted DWT and root MUSIC to extract heart rate (HR) hidden in the breathing signal.

With a shorter wavelength, the mmWave signal reflected from the human body provides finer-grained information [85]. FMCW is a class of frequently used mmWave for vital signs monitoring. *Vital-Radio* [86] leveraged an important property of FMCW that the reflection from different objects can be separated into different buckets with respect to their reflection time. *Vital-Radio* captured chest motion-induced phase change of the reflected FMCW to obtain accurate RR and HR estimation from up to three people in eight meters working range simultaneously. To monitor multiple people's breathing in a closer range, DeepBreath [87] applied the blind source separation and ICA to achieve RR extraction from eight subjects sitting tightly on a couch. In-home environments, flexible deployment for health monitoring is always desirable. Zhao et al. creatively mounted mmWave radar on a domestic service robot, enhanced mobility, and used deep neural networks to improve HR estimation accuracy [88]. Deep learning also enables RF signal to inference fine-grained vital signs, such as seismocardiography (SCG) [89], which is a series of micro cardiac events that conventionally require intrusive measurement performed by professional medical practitioners.

3.1.2. Via acoustic signal

Cross-sensing brings opportunities for widely equipped acoustic modules on wearable devices in vital sign monitoring. For non-contact respiration detection, Xie et al. calculated the RR from CIR of music and broadcast signals [90], Xu et al. achieved acoustic signal-based fine-grained breathing waveform estimation in a noisy driving environment [91]. Identifying respiratory diseases has great significance for public health, such as early-stage diagnosis of COVID-19. *SpiroSonic* [92] designed a contactless and user-friendly spirometry testing system using smartphone speakers and microphones to measure the users' chest wall motions. In order to obtain lung function estimation at a high level of accuracy, *SpiroSonic* adopted the Bayesian neural network, which demonstrated less than 7.7% error compared with medical spirometry equipment with bulky size and high costs in clinical studies. Qian et al. presented the acoustic cardiogram (*ACG*) system that enabled smartphone microphones and speakers with heartbeat rhythm sense [93]. Inspired by the RF-tracking system [37–39], the *ACG* system adopted FCMW to track the frequency shifts of inaudible acoustic signal caused by chest motions. Comprehensive clinical studies have validated the *ACG* system's high accuracy with a median heart rate estimation error of 0.6 beats per minute (bpm) and a median heartbeat interval estimation error of 19 milliseconds.

Recent advances in soft electronics have witnessed vital sign monitoring by contact acoustic sensing, such as ultrasonic signal-based cardiovascular events monitoring [94], wrist-worn MEMS microphone-based accurate HR monitoring [95], and clothes penetrable respiratory monitoring [96]. Among them, epidermal mechano-acoustic sensors have demonstrated various vital sign monitoring applications [97]. Ni et al. proposed a well-designed health monitoring device based on the mechano-acoustic signal obtained from a three-axis accelerometer [79]. Fig. 4(b) depicted the electronic components and flexible circuits encapsulated in silicone elastomer, which enabled simultaneous monitoring of multiple physiological processes, including energy expenditure, HR, RR, swallow counts, and talking time.

3.1.3. Via visual signal

The mainstream technology behind vital sign monitoring by ubiquitous cameras in wearable mobile devices is the remote PPG (rPPG) [98,99]. Based on a similar principle with conventional contact PPG, rPPG also estimates the blood volume pulse underneath the skin but treats ambient illumination as the light source and digital cameras as photodiodes [100]. Apart from a more comfortable user experience brought by its non-contact nature, rPPG also enables telemedicine applications [101]. As illustrated in Fig. 4(c), generally, there are three stages [80] for respiratory rate estimation in rPPG: first, skin pixels from all video frames are identified as the region of interest (ROI); second, the temporal color traces of these pixels are combined into a single temporal rPPG signal; finally, the rPPG signal will be used to analyze the respiratory rhythm. However, the accuracy of remote PPG is subjected to the

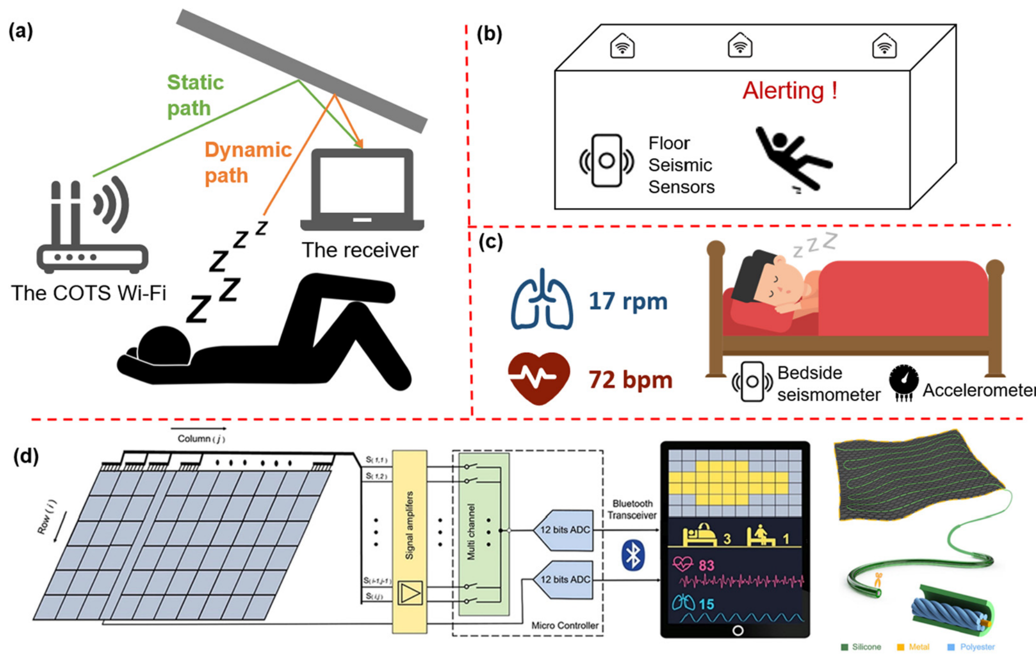

Fig. 5. RF and motion signal in the smart home for sleep monitoring and fall detection. (a) Wi-PSG using commodity Wi-Fi devices to monitor rhythmic movements during sleep [109]. (b) Vibration sensors deployed on the floor can locate the position of user falls [110]. (c) A bedside-mounted seismometer can provide contactless monitoring of vital signs and sleep posture [111]. (d) A real-time sleep monitoring system based on a flexible textile self-powered pressure sensor. Reproduced with permission [112]. © 2020 Elsevier

illumination change and subjects' movements. To improve the robustness in realistic conditions, Luguern et al. leveraged energy variance maximization to improve the SNR of the output trace [102], Huang et al. achieved rPPG in driving vehicles by spectral filter banks algorithms [103]. Furthermore, emerging deep learning algorithms such as multi-task learning [104], LSTM network [105], 3D-CNN [106], and GAN [107] are also empowering more robust rPPG. However, the facial image typically used for rPPG posed privacy concerns. Wang et al. proposed the single-element sensing for rPPG, not only prevented the privacy leakage, but also reduced the data storage and transmission throughput [108]. And a Soft Signature (SoftSig) based extraction algorithm was designed to evade the dependence of pulse extraction on facial skin area prior knowledge.

3.2. Smart home health services

Health and safety-related services such as sleep monitoring and falling detection are essential to smart home systems. Meanwhile, privacy and comfort are two critical considerations for the household environment. This section reviews RF signal and motion signal enabled non-intrusive sleep monitoring and fall detection as illustrated in Fig. 5.

3.2.1. Via RF signal

Continuous sleep monitoring is indispensable for early diagnosis of sleeping disorders like insomnia and obstructive sleep apnea-hyperpnea syndrome (OSAHS). The gold standard of sleep monitoring is in-clinic polysomnography (PSG). However, PSG requires dozens of cables connected with patients, which is not suitable for home use. Although wearable devices like smartwatches or smart wristbands can roughly monitor sleep parameters, users may feel uncomfortable wearing them to sleep or forget to wear them before sleep.

Liu et al. proposed *Wi-PSG* [109], the first rhythmic movement disorder detecting system based on home-use Wi-Fi infrastructure. Fig. 5(a) described that body movements turned the static line-of-sight propagation path to the dynamic path, which can be observed by the CSI changes. From the extracted time and frequency domain CSI feature, *Wi-PSG* trained a four-class SVM classifier that achieved 92% recognition accuracy. In 2018, Liu et al. further added fine-grained vital signs monitoring function to the *Wi-PSG* system and enabled sleep posture tracking of two people on the bed [113]. Zhang et al. adopted the statistical model to analyze all reflecting and scattering multipath, further achieving the recognition of rapid eye movement (REM) [114], which was only possible with dedicated medical instruments. Different from Wi-Fi-based solutions, *Body Compass*[115] and *EZ-sleep* [116] using mmWave antenna array achieved sleep posture detection and insomnia parameters, respectively. RFID tags can also provide a convenient sleep monitoring deployment. The hierarchical recognition scheme of *TagSheet* [117] can accurately generate the sleep posture image without any pre-training. Since the chest's cyclic motion periodically causes phase change of the tag's backscatter signal, *TagSheet* can also estimate the user's respiration rate, which is especially helpful for people suffering from sleep apnea.

Falling is becoming a significant health threat among seniors who live alone. Since the RF-based fall detection system does not require users to remind themselves to wear any additional device or recharge battery, it is a more practical approach for continuous monitoring. In 2018, Tian et al. introduced *Aryokee* [118], the first CNN architecture for RF-based fall detection. Wang et al. also exploit commodity Wi-Fi devices for fall detection [119]. In 2020, Ding et al. presented a fall detection system based on the Wi-Fi CSI framework using the RNN and provided a data analysis platform, web application programming interface, and user-friendly mobile app to provide a more comprehensive service to the elderly [120].

3.2.2. Via motion sensor signal

In home environment, non-wearable motion sensors can also realize fall detection, similar function with wearable motion sensor but serve in a more non-intrusive way. As shown in Fig. 5(b), Clemente et al. used a seismic sensor placed on the floor to achieve fall detection and alarming [110]. The user's location is estimated by the time-difference of arrival (TDoA) calculation of motion signal from all the synchronized seismometers distributed on different corners. An SVM is then utilized to differentiate the movement between falling, normal footstep, and other activities.

The seismometers also enable contact-free sleep monitoring, including body posture recognition, HR, and RR estimation [121]. In 2020, Li et al. proposed a bed-mounted seismometer-based system for sleeping parameters monitoring, as demonstrated in Fig. 5(c) [111]. The system applied ensemble EMD to decompose the vibration signal into different frequency ranges for HR and RR signal separation, and then seismocardiogram features were extracted to train a multi-class SVM for sleep posture recognition.

Textile-based triboelectric nanogenerator (TENG) sensors are becoming the emerging alternative to non-intrusive sleep monitoring. Due to its self-powered feature, even a small motion can generate an adequate electric signal for sensing. Zhou et al. weaved the TENG fiber into a textile substrate of bed sheet [112], as shown in the right part of Fig. 5(d). The functional textile has two distributions on the sheet; the grid-shaped part is used for sleep posture tracking, and the strip-shaped textile beneath chest position for HR and RR monitoring, illustrated in the left part of Fig. 5(d). The authors demonstrated that the system could effectively detect apnea during sleep and perform intervention promptly.

Gait information from wearable motion sensors is also a promising tool in diagnosing neurological disorders [122]. Greene et al. used shank-mounted inertial sensors to distinguish patients with early-stage multiple sclerosis. A 96.90% classification accuracy in distinguishing early-stage multiple sclerosis from controls convinced the excellent reliability [123]. Chang et al. performed a spatiotemporal gait analysis algorithm associated with the wearable system to identify patients' gait characteristics from stroke or Parkinson's disease [124]. Yoon et al. performed gait analysis to investigate gait characteristics in patients with freezing of gain (FOG) after hypoxic-ischemic brain injury [125].

3.3. Mental state monitoring

Mental state affects how people make decisions, commit actions, and tackle problems. People suffer from anxiety disorders such as panic disorder, post-traumatic stress disorder (PTSD), and social anxiety disorder, often experiencing fatigue, difficulty concentrating, and usually low productivity. Moreover, many researchers have linked mental disorders to many types of physical health problems [126]. This section reviewed how cross-sensing allows high-quality behavioral and biometric signals gathered from intelligent wearable devices for psychology research and promoting the public's mental wellbeing.

3.3.1. Via behavioral signal

People's emotions spontaneously manifested through their voices and movements, making it possible to estimate sentiment from their behavioral signal [127,128].

Human activity captured by motion sensors is helpful for emotion recognition. From the intelligent cushion's pressure sensor detection and wearable accelerometer reading, Gravina et al. proposed a feature level fusion to support emotion recognition [129]. Hashmi et al. used SVM and random forest algorithm to achieve 95% accuracy of six basic emotions' classification from smartphone's IMU reading [130].

The audio signal allows automatic detection and characterizes people's social activity as well as mental state. Zhu et al. combined SVM and DBN to achieve emotion recognition from Chinese speech [131]. Mosciano et al. fused multimodal data from physical sensors and acoustics sensors, achieving emotion recognition in a noisy scenario [132]. Kaya et al. used extreme learning machine classifiers to recognize eight emotional states among speakers in five different languages [133]. Chen et al. developed transfer learning for acoustic classification to establish interrelationships between the segmented voice features with anxiety level state [134]. Privacy protection is essential for audio-based methods. Yang et al. used four privacy-protected audio features to evaluate speech information in a naturalistic environment [135].

Combine the motion signal and audio signal, Gu et al. designed a wearable computing platform to extract and analyze speech and activity features, then used the integrated features to quantify the anxiety level by k-means classification [136]. Jin et al. also proposed a multi-sensing wearable device, which adopted attention-based block deep learning architecture to classify mental states [137]. The device captures users' speech and behavior signals to perform multi-feature classification and fusion analysis, obtaining optimum fusion weights of multiple emotional and behavioral features.

3.3.2. Via biometric signal

Insights about internal states of mind can be a valuable resource in determining mental health state, also can be used to prevent potential risks in extreme situations. Traditional methods such as surveys and interviews provide limited accuracy and reliability; therefore, acquiring biometric signals became an objective way to detect mental health issues.

Stress has negative impacts on psychological well-being; accurate measurements of stress levels help prevent stress and stress-related diseases [138]. Coutts et al. deployed an LSTM network and used HRV data collected from wrist wearables to predict stress levels [139]. The method achieved 85% classification accuracy, providing a good prediction on mental health measures. Zanetti et al. used ECG, EEG, and BVP signals acquired by low invasive wearable devices to perform stress detection, 84.6% accuracy was achieved from logistic regression and random forest classifiers [140].

EDA, recorded by measuring the conductivity of human skin, provides a good prediction for mental states. Setz et al. used a wearable EDA device to discriminate stress from the cognitive load, with an accuracy larger than 80% [141,142]. Ghandeharioun et al. performed an experiment that predicts the Hamilton depression rating scale using sensor data captured by E4 wearable wristbands and embedded sensors in an Android phone [142]. By applying machine learning techniques on the users' objective data such as EDA, sleep behaviors, phone usage, etc., the experiment found that poor mental health is caused by irregular sleep, less motion, and higher asymmetry of EDA between right and left wrists.

The RF devices can also capture people's biometric signals, therefore, infer their mental states. *EQ-Radio* [143] adopted FMCW radio to achieve comparable accuracy with the standard on-body ECG-based emotion recognition system; *Wi-Mind* [144] further leveraged the vital signs from the FMCW radio to assess cognitive load. *V2iFi* [145] installed an impulse radio in the vehicle to detect driver drowsiness and prevent road rage, two culprits for car accidents.

4. Authentication and security

As personal accessories, the wearables are tightly binding with their owner's identity, making them suitable tools for user authentication. Meanwhile, wearables collect the user's private and sensitive information during usage, which also poses many security attack opportunities. This section reviewed the cross-sensing enabled innovative authentication approaches by ubiquitous signals and discussed the possible information leakage from wearables.

4.1. User authentication

The ever-growing security issues in various mobile applications and smart devices create an urgent demand for reliable and convenient user verification methods. Traditional authentication methods request users to provide sensitive information (e.g., passwords and fingerprints), while the cross-sensing enabled authentication approaches leverage RF signal and acoustics signal without the user actively participate in the verification process.

4.1.1. Via RF signal

Several studies have reported the RF signal commonly seen in daily life can continuous and contactless validate the users' identities based on their biometric patterns.

Liu et al. reused the widely deployed Wi-Fi infrastructure to capture the unique physiological characteristics rooted in users' respiratory motions and provided a non-intrusive and continuous verification [146]. Heart motion can be used for continuous authentication as well. In 2017, Lin et al. presented *Cardiac Scan* [147], which identified users by unforgeable cardiac muscle self-excitation geometric and non-volitional features. Li et al. proposed *VocalPrint* [148], a resilient mmWave interrogation system, which exploited the skin-reflect RF signal's unique disturbance and analyzed the hidden vocal vibrations for user authentication. Besides, Kong et al. implemented *FingerPass*, which utilized CSI from nearby Wi-Fi signal to authenticate users via finger gestures [149].

Authenticating the legitimate users of wearable devices can be accomplished passively by monitoring the wearer's gaits. Arra et al. highlighted a method for authenticating by measuring the distances between multiple body-worn UWB transceivers [150]. Yang et al. proposed *MU-ID* [151], a gait-based authentication system using a single commercial off-the-shelf mmWave radar, which analyzed the user's unique gait patterns in terms of inter-lower limb distance, instantaneous limb velocity, step length, and duration. Since an individual's gait can also affect the frequency spectrum of Wi-Fi signal, Zhang et al. proposed *WiFi-ID* [152], which extracted unique features from the user's walking styles for user identification.

4.1.2. Via acoustic signal

As smart wearable devices' acoustic sensors are becoming more common than ever before, acoustic-based authentication shows good usability.

Gao et al. utilized the distinctive geometrical and physical features of the human ear canal and evaluated acoustic properties of in-ear sound waves reflection for authentication [153]. To ensure a cost-efficient authentication mechanism, Zou et al. proposed a new biometric authentication approach that utilized human's tooth click sounds of dental occlusion [154]. Furthermore, the acoustic signal can be used for signature verification as well. Chen et al. proposed *SilentSign*, which used speakers and microphones embedded in smart devices to facilitate a safe and efficient signature verification [155]. *SilentSign* measured the phase change of acoustic signal to track user's hand signature invisibly. Shi et al. proposed *WearID* [156] to address the security risks of voice assistant systems. Specifically, *WearID* associated motion sensors to validate the command voice through two domains (*i.e.*, the microphone and the motion sensor) to ensure that the voice came from the legitimate user. Chauhan et al. introduced *BreathPrint* [157], an acoustic-biometric signature based on unique breathing gesture variations of natural breathing, which combined three distinct personal breathing behaviors: deep breathing, regular breathing, and sniff, to identify users through the wearables' microphones.

4.1.3. Via biometric sensor signal

Beyond interpreting users' health conditions, wearable biometric sensor signals also reflect users' unique biological features. Fig. 6 shows the paradigm of biometric sensor signal-based continuous user authentication, which minimizes user's involvement in the verification process.

The PPG signal possesses distinctive characteristics for identification and is becoming increasingly available from wearables.

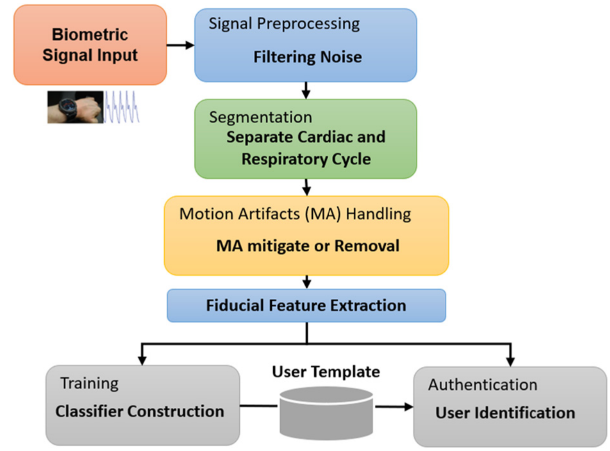

Fig. 6. The paradigm of biometric signal-based authentication.

Zhao et al. presented a motion artifact (MA) robust authentication system utilizing the built-in PPG sensor of commodity smartwatches [158,159]. Cao et al. introduced *PPGPass* [160], an innovative portable two-factor authentication method based on wrist-worn PPG signal. To achieve secure and non-intrusive authentication, they proposed a two-stage algorithm to differentiate heart rate from MA signal, which does not require users to stay still throughout the authentication process. Furthermore, Bastos et al. presented a double authentication model, which analyzed both PPG and ECG signals to avoid the bias of single bio-signal and enhance security for validation [161]. Karimian et al. explored non-fiduciary features of PPG signal for authentication, which is robust to noise in signal landmarks [162]. Khan et al. utilized EMG signal to track the muscular action potentials in the neck area throughout the speech [163]. The results demonstrated a maximum performance of 95.3% by applying the quadratic SVM classification model for all ten categories.

Heartwave as a biometric mechanism that can be easily obtained via wearable ECG sensors has a great capacity to provide continuous authentication. Lim et al. proposed a heartwave-based authentication approach that increased function extraction reliability by using an aggregate of DBN with different parameters. With only 30% training data, the algorithm was able to accomplish a recognition accuracy of 98.3% [164]. Furthermore, Lim et al. described a biometric recognition system focused on an adaptive heartrate-derived heartwave signal [165]. They designed a heartwave extraction algorithm integrating a hybridized DWT approach with heartrate-adaptive QT and PR intervals. The classification was performed using a hybridized GMM-HMM classification system, which achieved true positive rate of 0.89 and 0.11equal error rate.

4.2. Snooping via wearables

Sensory systems on wearables and smart devices can enhance users' experience. However, sensitive information, such as personal information or passwords that are frequently entered on smart devices may leak inadvertently. For example, some mobile operating systems do not restrict apps to access readings from microphones and motion sensors (*e.g.*, accelerometers and gyroscopes).

4.2.1. Via motion sensor signal

Prior research had accomplished motion sensor-enabled snooping in context-aware conditions, including 1) the last keystroke on a fixed 'enter' button, 2) the known keyboard size, 3) the lateral keyboard plane. In 2018, Liu et al. revealed the further threats of typing privacy leakage in simplistic context-free circumstances associated with the regular use of portable devices [166]. Furthermore, Li et al. proposed *ClickLeak* [167], an effective multimodal

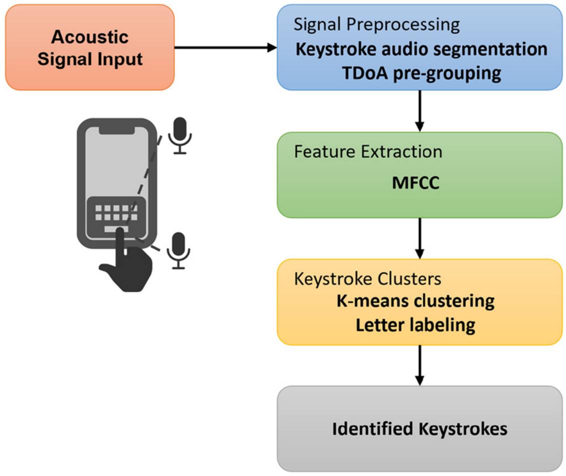

Fig. 7. Snooping user keystroke input from acoustic signal.

side-channel fingerprint identification scheme that predicts the PIN code/password entered on the numeric keypad. *ClickLeak* used the microphone and acceleration sensors from mobile phones to evaluate the start and end times of keyboard strokes, while the time series of Wi-Fi CSI was utilized to determine the keyboard strokes. Furthermore, Wang et al. demonstrated a wearable system with capabilities of distinguishing distances at millimeter level and direction of the user's fine-grained hand motions. This work enabled attackers to replicate the user's hand trajectories and further retrieve the confidential key entries [168].

The MEMS gyroscopes installed in mobile phones have the ability to transform the motion signal into an acoustic signal. Although only a low-frequency ($<$200 Hz) acoustic signal can be restored, it is sufficient to recognize voices and interpret speeches [169]. In addition, Wang et al. observed that the motion sensor from a smartwatch can significantly leak typing information [170]. Using the Bayesian inference model, the *Mole* system has been successfully associated motion signal of typing with language pattern and realized a training-free ranking of possible word short-lists. In addition, Wang et al. introduced a passcode inference method, *WristSpy*, which analyzed the possibility of whether the user's PIN/pattern disclosed from a single wrist-worn wearable interface during digital payments under various passcode input cases [171]. Lastly, Jiang et al. developed a deep learning-enabled handwriting eavesdropping architecture, which utilized the motion signal leaked from smartwatches or wristbands while users were writing privacy information [172].

4.2.2. Via acoustic signal

Fig. 7 illustrates that information could be leaked by the sound of keyboard tapping or handwriting, which exposes the possibility of acoustic side-channel attacks [173–176]. The exponential development of mobile devices exacerbates the possibility of audio-based snooping in public settings.

In 2019, Lu et al. demonstrated *KeyListener* [177] to prove the feasibility of indirect snooping attacks. *KeyListener* estimates keystrokes on touch screen's QWERTY keyboards using mobile audio systems. Lu et al. analyzed the attenuation of the acoustic signal obtained by the mobile's microphones and found the keystroke fingers of a user could be targeted and localized. In 2015, Liu et al. proposed the first training-free keyboard typing snooping method based on the acoustic signal from a single mobile device [178]. Their study demonstrated that mobile's built-in audio system could differentiate finger location variations at a millimeter level, which allows the system to estimate the location of typing on a keyboard in front of it. To distinguish multiple strokes on the same key, the keystrokes were grouped by TDoA calculations. Similarly, Xiao et al. found that as a user types on a smartphone's touchscreen, all microphones can catch the sounds produced by vibrations from fingers tapping on the phone screen, and these collected sounds are adequate to predict the keystrokes of the user [179]. Yu et al. proposed *WritingHacker*, a handwriting snooping framework [180]. *WritingHacker* used smartphones to obtain the users' handwritings' acoustic signal and extract handwriting features for SVM-based analysis.

5. Summaries and perspectives

In this paper, an organized overview of wearable applications realized in cross-sensing has been proposed. Moreover, a taxonomy that categorizes the multiple functions of the ubiquitous signals has been included. This section summarized the above innovative works and put forward our perspectives on future works.

As seen in previous sections, a new terminology has been used to refer to the concept of enabling the sensing capability beyond the signal's original usage and the devices' original design. The term "**cross-sensing**" is broad, whereas we focus it on the fulfillment of wearable applications. In the context of wearables, cross-sensing brings three distinct advantages. First, cross-sensing allows fewer electronic components to fulfill more functionalities, which reduces space occupation, hardware cost, and energy consumption for sensing purposes. Second, cross-sensing enables broader applicability, expands the application domains and usage scenarios. Finally, specific tasks delivered by cross-sensing may exhibit some unique merits; as an example, the pervasive RF signal can facilitate contact-free and continuous health monitoring.

Although the variety of signals can be utilized to achieve cross-sensing, all the works we have reviewed are based on the same principle: they are the commonly seen signals in peoples' daily lives. A summary of multiple functions (Table 2) delivered through the three most representative signal categories can be found in Table 3–5. The abbreviations of signal processing and machine learning algorithms used in these tables are consistent with Table 1 in the first section.

As a fast-growing field, numerous solid works have been reported based on the multi-functional use of ubiquitous signals, especially for wearable applications. However, there are still potential improvements to be made so that further usages of sensors can be exploited, and hence more work needs to be completed in this emerging area. As such, some research topics and trends can be considered, which are summarized as follows:

- *Emerging materials and sensing devices*. The sensing capabilities of the cross-sensing techniques are determined by the adopted sensors and their working mechanism. To achieve better performance, new types of sensors based on emerging materials and mechanisms can be considered and utilized in the cross-sensing tasks. At the same time, the convenience and non-invasive properties should be taken into consideration when designing the devices. Thus, smart wearable textiles have emerged as an alternative.
- *Self-powering and energy harvesting techniques*. Batteries are the mainstream energy source in the majority of wearable devices. However, battery usage also causes many problems. Recharging the battery on a regular basis could be an annoying routine, especially for travelers and forgetful people, let alone its negative impact on the environment when it was not recycled or dismantled properly. Wearable devices with self-powered nature or energy harvesting technologies, including triboelectric nanogenerator [181], piezoelectric generator [182], solar cells, and supercapacitors [183], may prolong the

Table 2
Abbreviation of multiple functions addressed by cross sensing

Abbreviations	Definitions	Abbreviations	Definitions
PT	Position Tracking	**SCG**	Seismocardiogram
ST	Body Skeleton Tracking	**FD**	Fall Detection
VII	Virtual Input Interface	**SPM**	Sleep Posture Monitoring
GR	Gesture Recognition	**SSM**	Sleep Stage Monitoring
RR	Respirate Rate monitoring	**ER**	Emotion Recognition
HR(HRV)	Heart Rate (Heart Rate Variability) monitoring	**AT**	Authentication
BP	Blood Pressure	**SN**	Snooping

Table 3
Multiple usages of the wireless communication signal

Reference	Sensing approach	Signal processing & machine learning algorithms	Functions	Support multi-users	Average accuracy
WiTrack [37,39]	mmWave	FFT, Kalman Filter	PT [37,39]	× [37], √ [39]	±30 cm [37], ±11.7 cm [39]
RF-Pose3D [38]	mmWave	CNN, RPN	ST	√	±4.4 cm
Widar [40,41,57]	Wi-Fi CSI	STFT, PCA [40], Graph-based Path Matching [41], CNN, RNN[57]	PT [40,41]/GR [57]	×	±38 cm [40], ±75 cm [41] 92.7% among 4 gestures [57]
mmTrack [42]	mmWave	k-means	PT	×	±9.9 cm
LiSense [46]	VLC System	FFT, Kalman Filter	ST	×	±10°
StarLight [47]	VLC System	FFT, Kalman Filter	ST	×	±13.6°
PIXEL [49]	VLC System	Binary color shift keying	PT	√	±30 cm
SignFi [58]	Wi-Fi CSI	CNN	GR	×	94.81% among 276 gestures
AirDraw [59]	Wi-Fi CSI	PCA	PT	×	±2.2 cm
RF-ECG [81]	RFID	DWT, PCA, Kalman Filter	HRV	√	±26.3 ms
ResBeat [82]	Wi-Fi CSI	Exponentially weighted moving average	RR	×	90%
Gao et al. [83]	Wi-Fi CSI	DAM, DBSCAN	RR	√	97.5%
PhaseBeat [84]	Wi-Fi CSI	DWT, Root MUSIC	RR/HR	√	±0.25 rpm, ±1.19 bpm
ViMo [85]	mmWave	ACF	RR/HR	√	±0.19 rpm/±1 bpm
Vital-Radio[86]	mmWave	FFT	RR/HR	√	±0.09 rpm[1]/±0.95 bpm[2]
Deep breath [87]	mmWave	ICA	RR	√	±0.03 rpm
mBeats [88]	mmWave	FFT, customized DNN	HR	√	±3 bpm
RF-SCG [89]	mmWave	CNN, U-Net model	SCG	×	98.71%∼99.74%
Wi-PSG [109]	Wi-Fi CSI	SVM	SSM	×	92%
Liu et al. [113]	Wi-Fi CSI	K-means, PCA, SVM, KNN	SPM/RR/HR	√	> 90%/±0.4 rpm/±2 bpm
SMARS [114]	Wi-Fi CSI	ACF, SVM	SSM/RR/HR	×	88%/±0.47 rpm/±2.92 bpm
Body Compass [115]	mmWave	customized DNN	SPM	×	87%
ez-sleep [116]	mmWave	HMM, CNN	SSM	√	±10.3 min per night
TagSheet [117]	RFID	PCA, FFT	SPM/RR	×	96.7%/±0.7 rpm
Aryokee [118]	mmWave	CNN	FD	√	94%
WiFall [119]	Wi-Fi CSI	SVD, SVM, Random Forest	FD	×	94%
Ding et al. [120]	Wi-Fi CSI	DWT, RNN	FD	×	93%
EQ-Radio [143]	mmWave	SVM	ER	√	87% among 4 emotions
Wi-Mind [144]	mmWave	FFT, Random Forest, Naive Bayes, SVM	ER	×	83% among 2 cognitive states
V2iFi [145]	mmWave	FFT	RR/HR/HRV	√	±0.2 rpm/±1.6 bpm/±100 ms
Liu et al. [146]	Wi-Fi CSI	FWPT, EMD	AT	×	93%
Cardiac scan [147]	Doppler radar	DTW, SVM	AT	×	98.61%
VocalPrint [148]	mmWave	DCT, TPCC, MFCC, GMM, SVM, HMM	AT	×	96%
FingerPass [149]	Wi-Fi CSI	SVM, LSTM network, inverse FFT, SVDD	AT	×	91.4%
Arra et al. [150]	UWB	MST, k-NN, k-means	AT	×	90%
MU-ID [151]	mmWave	FFT, CNN	AT	√	97% (1 person) ∼ 92% (4 persons)
WIFI-ID [152]	Wi-Fi CSI	CWT, FFT	AT	√	93% (2 persons) ∼ 77% (6 persons)

1: rpm – respiratory per minutes; 2: bpm – beats per minutes.

battery life or even replace the battery as the primary energy source.

- *Integrated circuit and computer architecture design*. The current cross-sensing research for wearable applications is mostly deployed with the general-purpose chip and circuits. With the explosive demand increase, the application-specific integrated circuit (ASIC) based chips can be designed and developed to realize the sensing, computing, communication, and storage while achieving higher energy and computing efficiency. The open-source architectures and tools, for example, RISC-V, have demonstrated outstanding potential and attracted significant interest from both academia and industry. Moreover, the emerging neuron-synapse integrated circuit and near-sensor analog signal processing scheme with low energy consumption [184,185] may reveal its advantages in promoting intelligent applications on wearables.
- *Customized sensing and learning algorithms*. The sensing and learning algorithms should fully consider the wearable scenarios' characteristics and be customized to the wearable computation platform. Due to the limitation of cost, size, and energy consumption, it is impractical for wearable devices to adopt high-accuracy sensors with a large sampling rate. Multimodal data fusion or multimodal learning can acquire complementary information from a different domain; the knowledge shared in each modal data is jointly utilized, thereby enhancing the effectiveness and quality of sensing tasks. The wearable computing platforms have limited computing power and storage, which poses challenges to complete

Table 4
Multiple usages of acoustic signal

Reference	Sensing approach	Signal processing & Machine learning algorithms	Functions	Support Multi-users	Average Accuracy
TapSkin [60]	Mic. + IMU	MFCC, SVM	VII	×	90.69%
Acustico [53]	Mic + IMU	Time difference of arrival analysis	PT	×	±7.57 mm (x-axis), ±4.62 mm (y-axis)
ViType [54]	Piezoceramics	k-NN	VII	×	95%
SoundWrite [61]	Mic.	FFT	VII	×	90%
WordRecorder [62]	Mic.	STFT, CNN	VII	√	81%
Ubiquitous Writer [63]	Mic. + speaker	MFCC, k-NN	VII	×	93.75%
AcouDigits [64]	Mic. + speaker	FFT, k-NN, SVM	VII	×	91.7%
EchoWrite [65]	Mic. + speaker	STFT, DTW	VII	×	95.4%
LLAP [66]	Mic. + speaker	EMD, EMA	PT/VII	×	4.6 mm/92.3%
WritePad [67]	Mic.	WT, CNN	VII	×	95%
VPad [68]	Mic + speaker	SOFT	PT/VII	×	±1.55 cm/90%
FingerSound [69]	Contact mic. + IMU	MFCC, SVM, k-NN, DTW	GR	×	92.46∼98.19% among 42 gestures
IPand [70]	Mic.	STFT, MFCC, CNN	GR	×	83% among 12 thumb gestures
HCI on the table [71]	Mic.	MFCC, CFCC, SVM	GR	×	93.2% among 7 thumb gestures
UltraGesture [55]	Ultrasonic sensor	STFT, CNN	GR	×	97% among 12 thumb gestures
SoundTrak [72]	Mic + speaker	FFT	PT	×	±1.3 cm
CAT [73]	Mic. + IMU	STFT, ADMM	PT	×	±3.8 mm
MilliSonic [74]	Mic + speaker	FFT	PT	√	±2.6 mm
FM-track [75]	Mic + speaker	Customized chirp analysis algorithm	PT	√	±1.1 mm
Strata [76]	Mic + speaker	FFT	PT	×	± 6 cm
Vernier [77]	Mic + speaker	DW-PC	PT	×	±2 mm
Earphone Track [78]	Mic + speaker	HT, FFT	PT	×	±6.9 mm
Xie et al. [90]	Mic. + speaker	Channel impulse response estimation	RR	√	±0.5 rpm
Breath Listener [91]	Mic. + speaker	VMD, HT, GAN	RR	×	± 0.11 rpm
Spiro Sonic [92]	Mic. + speaker	Customized ANN	Spirometry	×	±10% with clinical spirometry
ACG [93]	Mic. + speaker	Expectation maximization	HR	×	±0.6 bpm
Sharma et al. [95]	Mic.	FFT, STFT, K-means	HR	×	± 0.28 bpm
Cotur et al. [96]	Mic.	DTW	HR/RR	×	±6 bpm
Rogers et al. [97] [79]	Accelerometer	FFT, STFT	RR/HR	×	±0.3 rpm/±2.8 bpm
Zhu et al. [131]	Mic.	DBN, SVM	ER	×	95.8% among 6 emotions
EarEcho [153]	Mic. + speaker	SVM	AT	×	97.6%
BiLock [154]	Mic.	MFCC, SVM	AT	×	95%
SilentSign [155]	Mic. + speaker	SVM	AT	×	98.2%
WearID [156]	Mic. + IMU	Discrete time STFT	AT	×	99.8%
BreathPrint [157]	Mic.	GFCC, GMM	AT	×	94%
Keylistener [177]	Mic. + speaker	FFT	SN	×	90%
Liu et al. [178]	Mic.	MFCC, K-means	SN	×	94%
Xiao et al. [179]	Mic.	CNN	SN	×	92%
Writinghacker [180]	Mic. + IMU	SVM	SN	×	60%

Table 5
Multiple usages of motion signal

Reference	Sensing approach	Signal processing & Machine learning algorithms	Functions	Support Multi-users	Average Accuracy
Clemente et al. [110]	Seismometer	SVM	PT/FD	×	±28 cm/95.14%
Helena [111]	Seismometer	SVM, Ensemble EMD	HR/RR/SPM	×	±1.6 bpm/±0.3 rpm/90.3% among 4 postures
Zhou et al. [112]	Textile TENG	*N/A*	HR/RR/SPM	×	± 1 bpm
Gravina et al. [129]	Pressure sensor + IMU	PCA, FFT, HMM	ER	×	91.8% among 4 emotions
Hashmi et al. [130]	IMU	SVM, Random Forest, FFT, DWT	ER	×	86% among 6 emotions
aleak [166]	IMU	FFT	SN	×	94%
ClickLeak [167]	IMU, Wi-Fi CSI, Mic.	PCA, k-means, HT, DTW, STFT, kNN	SN	×	83%
Wang et al. [168]	IMU	Savitzky-Golay filter, HMM	SN	×	90%
Gyrophone [169]	Gyroscope	HMM, STFT, SVM, GMM, DTW	SN	×	77%
MoLe [170]	IMU	Kalman Filter, Bayesian Inference	SN	×	50%
WristSpy [171]	IMU	Savitzky-Golay filter, SVM	SN	×	92%
Motion Eavesdropper [172]	IMU	Multimodal CNN, LSTM network	SN	×	71.9%

complex tasks. Compressed machine learning [186] with low complexity and high efficiency can achieve satisfactory performance; distributed learning [187] allows the extra nodes to participate in computation; transfer learning [188] uses prior knowledge to accelerate model training for new tasks.

- *Privacy and security*. As wearable applications are often involved with sensitive personal information, the privacy and security issues of the wearable sensors and systems will arise and must be carefully dealt with, especially when incorporated with deep learning progress. Federated learning [189], featured data privacy, security, and legal compliance, can realize joint modeling and improve the performance of AI models. Allow users to share personal data with confidence and solve the problem of "Isolated Data Island".

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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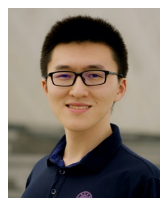

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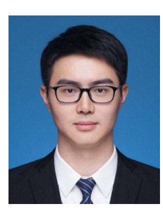

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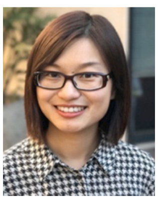

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