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Vibration sensing-based human and infrastructure safety/health monitoring: A survey

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ABSTRACT

Current sensor technologies enable the passive and continuous monitoring of human behaviors as well as infrastructures to ensure personal safety and assess individual health state. One passive technology that has the potential of gathering personal data is the vibration sensor. In this paper, we carry out an extensive survey of the current vibration-based sensing technologies for human and infrastructure safety as well as health monitoring. These technologies utilize structural and bodies vibration as a source of data, and they can be incorporated in wearable or non-wearable devices. Furthermore, the vibration sensing technology utilizes low-cost and low-power sensors, which make it attractive for indoor and outdoor monitoring. We have classified the technologies into five categories: vibration-based sensing for assessing human health, recognizing personal behavior, inferring occupancy information, evaluating personal safety, and monitoring infrastructure health. In each category, we also classify the approaches that utilize single and multiple sensors. Moreover, we discuss the different types of signal processing and machine learning techniques that are applied to each approach.

1. Introduction

The use of sensor networks in areas such as healthcare, human behavior, occupancy information, personal safety, and infrastructure health monitoring is growing at a fast pace. In the health area, the use of appropriate sensors provides multiple benefits: First, they allow monitoring of patients/subjects in real-time and continuously. Wireless sensors can replace expensive and cumbersome wired telemetry systems [1]. Second, sensors allow the collection of long-term database and trend analysis of patients, which can be beneficial either to submit the data directly to physicians, or correlate bio-sensor readings with other patient information, for example, behavioral monitoring in smart homes [2].

In this area, recognition of movements and activities such as sitting, standing, lying, walking, and running can assist in the adoption of satisfactory health interventions and improved care. There are multiple approaches that aim to recognize human behavior using different types of sensors and devices, including smartphones [3–5], wearable accelerometers[6–8], motion sensors[9–11], cameras [12–14], etc. In the occupancy information inference, sensors can track person's activities for detecting abnormal behaviors that can represent a potential risk [15]. For example, different kinds of sensors are used to detect occupants inside the home using PIR sensors [16], which sense the motion of objects, magnetic door sensors [17] for occupancy state, and cameras modules [18] to capture images of occupants. In the addition to the above, sensors play a critical role in overseeing infrastructures (e.g. analysis of buildings) to provide efficient and timely detection of deterioration [19]. In building monitoring, fiber optic sensors [20], nanotube sensors [21], and accelerometer sensors [22] have been used to determine the health of civil infrastructures.

An emerging monitoring technology, **vibration sensors**, considered non-intrusive (no causing disruptions in normal activities), is arising in sensor research for health and safety applications. Many environments, machinery, motors, and people cause periodic motions of structures to induce vibrations into other devices and structures located nearby [23]. The study of vibration measurements would be beneficial to the understanding of patterns and signals from human/infrastructure activities. Vibration measurements are complex because of its many components (displacement, velocity, acceleration, and frequencies). In addition, each component in the corresponding signals can be measured in many different ways; for example, peak-to-peak, maximum/minimum peaks, average, root-square mean (RMS), etc. These signals can

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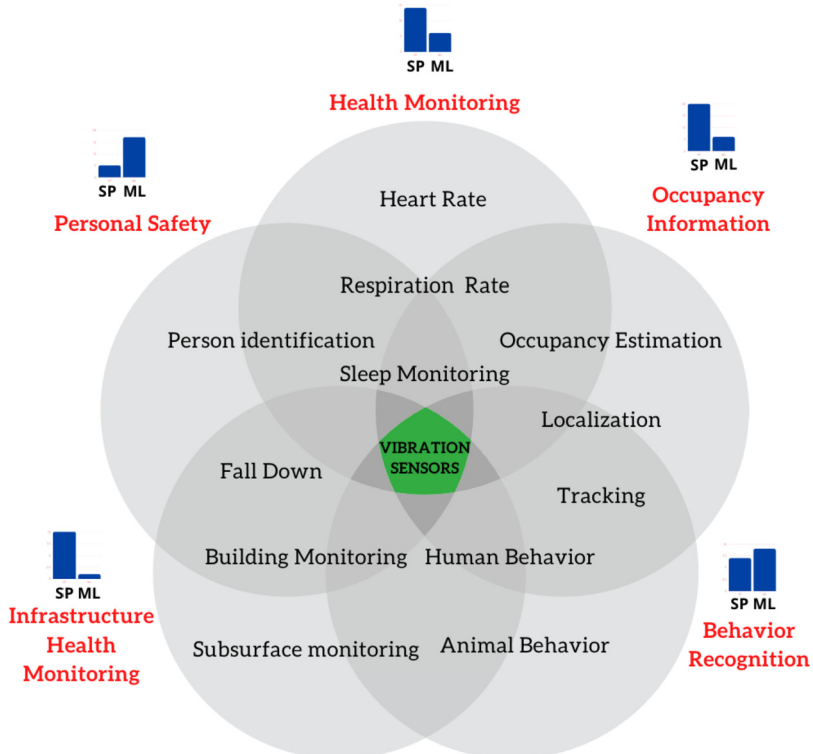


Fig. 1. Example of vibration-based sensor applications on health assessment, activity characterization, infrastructure monitoring, personal safety, and behavior recognition. Note that the approaches that uses machine learning (ML) also may use signal processing (SP) techniques in the preprocessing and feature extraction stages. The total number of approaches that use pure SP is 68, the number of ML is 40 and from those almost 90% uses SP as well.

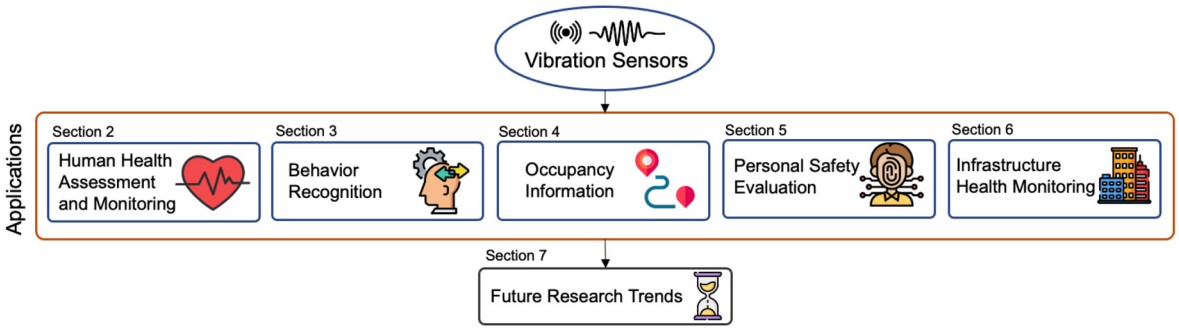
also be measured in the time domain (real-time, instantaneous measurements with an oscilloscope or data acquisition system) or frequency domain (vibration magnitude at different frequencies across a frequency spectrum), or just a single numerical value for "total vibration."

In this paper, we carry out an extensive survey of the current vibration-based sensing technologies for human, infrastructure safety and health monitoring that use vibration measurements only. We have classified the vibration-based technologies into five categories: assessing human health, recognizing personal behavior, inferring occupancy information, evaluating personal safety, and monitoring infrastructure health. In each category, we also classified the approaches that utilize single and multiple sensors and inter-node communication, as well as the different types of signal processing and machine learning techniques that are applied to each approach. Furthermore, within each category, we present different types of applications (e.g. occupancy estimation, person identification, heart rate estimation, building monitoring, etc.) Fig. 1 shows examples of vibration-based applications in each studied category. On top of each category name, there is a bar graph that indicates the proportion of applications that use pure signal processing (SP) techniques or machine learning (ML) approaches. Note that the approaches that use ML also may use SP techniques in the preprocessing and feature extraction stages. In this paper, we consider "pure signal processing techniques" to those approaches that apply time and/or frequency domain analysis to the signals without the use of ML or deep learning methods. On the other side, we consider and categorize approaches like machine learning approaches, those that apply ML even if they have applied SP for the preprocessing or the feature extraction process. In this figure, the trend of data analysis technique per category is clear. The use of SP approaches is more frequent in health monitoring, activity characterization, and infrastructure monitoring, whereas the ML approaches are more frequent in personal safety and behavior recognition applications. Also, note that some of these applications may lie in multiple categories as they can be used for multiple purposes.

The rest of the paper is organized as follows: Section 2 introduces the research works for monitoring and assessing human health that has an impact on the healthcare system. In Section 3, we present the vibration-based approaches to recognize and classify behavior. The approaches to inferring occupancy information are presented in Section 4. Section 5 introduces the applications for personal safety such as person identification and occupancy estimation. Section 6 presents vibration-based approaches for building and infrastructure monitoring. We elaborate on the future of vibration-based the technologies in Section 7, and we present the conclusion of our research in Section 8. See Fig. 2.

2. Human health assessment and monitoring

Vibration and mechanical-vibratory signals are known to contain essential information for clinical diagnosis and healthcare applications [24–27]. As explained in [28], the mechanical waves that propagate through the body due to natural physiological activity reveal characteristic signatures of individual events, such as body orientation (about 0-0.1 Hz), respiration (about 0.1-0.5 Hz), pulse (about 0.4-2 Hz), gait, and locomotion (about 0-5 Hz) [24,29]. Medical applications can take advantage of these measurements, especially in the area of remote health monitoring [24,29,30]. Currently, the investigation on vibration signals for health monitoring is mainly focused on the cardiac effects. However, by combining different respiratory modulations on morphology and the frequency of the signals, the respiratory rate (RR) can be measured and has a great potential for detecting respiratory diseases like apnea or shortness of breath [31]. The seismocardiogram (SCG) signals obtained by this type of sensors represent the local vibrations of the chest wall in response to the heartbeat [32]. The reflection



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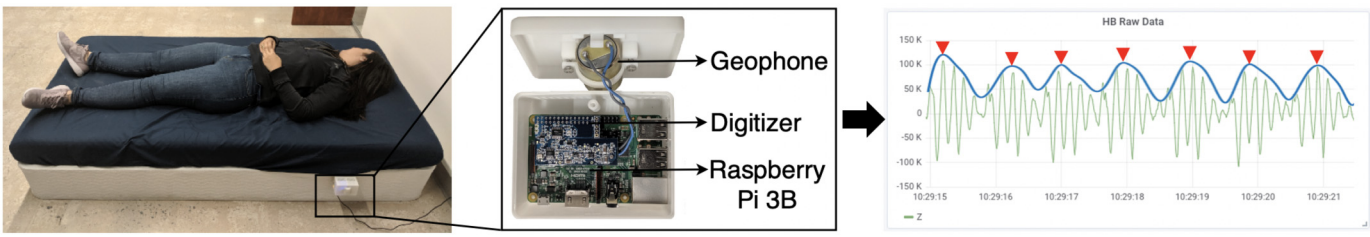

Fig. 3. Heart rate monitoring using a geophone attached to a bed. Raw Data from a geophone that show the different stages of cardiac cycle. Adapted from [35].

of the minor body movements caused by cardiorespiratory effects generates several independent peaks in the SCG. These peaks represent the cardiovascular activity in different phases of the cardiac cycle [33] and have been widely studied to extract the heart rate (HR) [34–36]. Besides, by changing the position and amplitude of these peaks, respiration influences the waveform and amplitude of the SCG [37,38], which led to RR detection [35,39]. Fig. 3 shows an example of data that can be collected by a vibration sensor located under a mattress when a person lay down on the bed and the peaks that represent the cardiac cycle [35].

Some vibration sensors (e.g., geophones) can provide ballistocardiograph (BCG) signals. BCG refers to the measurement of the repetitive human body displacement caused by the heartbeat and blood ejection [40]. BCG provides valuable information about cardiovascular function, such as the myocardial contractility [41]. The main advantage of BCG is that it can provide a non-intrusive monitor of the heart as no sensors need to be attached to the body. The HR and RR have been measured using BCG with different sensors like force sensors [42,43], air or water pressure sensors [44–46], accelerometer sensors [47], and geophone [48].

Besides HR and RR, other studies have made efforts to estimate more complex vital measurements including blood pressure [49,50] and knee health monitoring [51] using vibration. Furthermore, the analysis of sleep patterns – movements, bed occupancy, and positions on the bed can also be studied using vibration signals [35,52]. In this section, we present the data analysis techniques that have been used for health monitoring with vibration sensors. We present the works that have used one or multiple sensors to estimate the vital sign measurements. Differentiating the number of sensors in these applications can provide a platform for new ideas of using a sensor network to share information of partial results in the estimation process and enable optimization processes in these solutions.

In this section, we explore the different signal processing and machine learning techniques that have been used to estimate vital signs and health monitoring with vibration sensors (Section 2.1). We also present the different types of sensors and/or sensor networks used in each approach (Section 2.2).

2.1. Data analysis techniques

Some of the most important applications in health assessment and monitoring are related to estimating heart rate, respiration rate, and evaluating person's sleep patterns. The type of data analysis technique varies from application to application. Here, we survey the most common methods used for assessing HR and RR (Section 2.1.1), sleep monitoring (Section 2.1.2), and gait analysis (Section 2.1.3).

2.1.1. HR and RR estimation

Initially, the estimation of HR and RR was utilizing specialized hardware devices. In one prior study [53], Mack et al. designed a vibration sensor consisted of an ultra-sensitive piezoelectric transducer that was able to capture low-frequencies responses to provide HR and breathing information. Different signal processing techniques were applied to enhance the raw data and separate the HR and breathing information including low-pass anti-aliasing filter [54], instrumentation amplifier, bandpass filters [55], and non-inverting amplifiers. The sensor was placed under the chest. The counting of the HR was performed manually from the filtered signal and compared to a commercial oximeter with an error of $\pm 5\%$. Later, in 2011, Dinh et al. [56] presented the design and testing of a heart rate sensor using a low-cost accelerometer. The sensor included a small-sized triple-axis accelerometer (MMA7260QT), a circuit, and an amplifier to process SCG signals. The accelerometer was mounted on a printed circuit board and taped on the chest of the participants. The signal processing techniques were made on hardware and included the two-stage filtering of the signal with a low pass filter with a cut-off frequency of 40 Hz. Then, a hardware timer was used to measuring the digital pulse by capturing the negative edges of the z-axis acceleration signal and represents the heartbeat.

Since 2016, the approaches for estimating HR and RR with vibration sensors have been oriented to apply software signal processing and machine learning techniques with off-the-shelf seismometers and geophones. In 2016, Jia et al. [48] were the first to propose a bed-mounted geophone-based heartbeat monitoring. In this study, authors use an SM-24 Geophone Element [57], an amplifier [58], and an Analog-to-Digital Converter (ADC) placed under

the mattress to extract the heartbeat of the person on the bed. The signal was processed in the following way. First, the authors computed an FFT on the geophone signal to find out whether there is a clear separation between heartbeats and body movements in the frequency domain. After experimentation, the FFT information suggested the application of a low-pass filter with a cut-off frequency between 6 and 10 Hz to effectively separate heartbeats and body movements. Then, a Sample Auto-correlation Function (ACF) [59] was applied to extract periodicity from the time series. The peak finding algorithm developed by Thomas C. O'Haver [60] was then applied to locate peaks in the sample ACF results. Those peaks were considered the heartbeats. However, the authors applied an optimization technique lo take only the first 20% of the peaks from the sample ACF to calculate the average heartbeat interval. The average error of the approach was 1.30% when the subjects did not move on the bed, and 3.87% when the subjects moved.

In 2018, Li et al. [39] proposed a methodology to extract HR and RR using a seismometer. For HR, the authors proposed a Local Maxima Statistics (LMS) method, and for RR, they proposed an Instantaneous Property from the Oscillatory Analysis. The main difference with [48] is that the strict periodicity property of the heartbeat is not required. In the LMS, when the peaks are generated by the heartbeat, the point is defined as the local maximum within an interval. To avoid interference produced by the filtering and ACF, the authors then applied an empirical truncate statistics analysis method to eliminated false peaks. In the oscillatory analysis for estimating RR, the oscillatory analysis technique synchrosqueezed wavelet packet transform (SSWPT) [62] is applied to extract instantaneous properties of the respiration. Then the SSWPT is used to obtain an instantaneous property estimation of the RR with the methods in [62–64]. Visual comparisons between results and peaks seem to match, but no further error measurements were provided.

Later, in 2020, Clemente et al. [35] present a comprehensive sleep monitoring system called "Helena" that includes the estimation of HR and RR while the person is in bed. A geophone of 100 Hz was used in conjunction with an embedded system that enables the real-time estimation of the vital signs. This is the first work that incorporates an end-to-end real-time system using vibration signals for HR and RR. The authors first prepared the signal from the geophone by applying notch filters [65] to suppress the noise components with iso-dominant-frequencies; then, a bandpass filter was applied with 0.1 Hz low-cut frequency and 8 Hz high-cut frequency to extract target vibration signals. To extract the HR, instead of using an LMS method as proposed in [39], the authors proposed an envelope-based HR estimation method. In this method, the envelope of the filtered signal is estimated and the peak detection is done over the envelope curve, which avoids the application of the ACF. To estimate RR, the authors proposed a double-envelope methodology in which the detected peaks of the HR (first-envelope) are used as the respiratory modulation signal by extrapolating them. Then a new envelope of the signal is obtained and count the peaks to estimate the respiratory rate. The results were compared with a cleared-FDA device, the Apple Watch Series 4 in a comprehensive study with multiple people in multiple environments, types of mattresses, and types of floors. The errors were about ± 2.41 beats-per-minute (bpm) and ± 0.89 respiration-per-minute (rpm) for HR and RR respectively. Later the same year, Li et al. [52] presented a variation of the "Helena" methodology by estimating HR and RR using an Ensemble Empirical Mode Decomposition (EEMD) method [66]. In this method, the signal is pre-processed using a bandpass filter with the same frequency than [35]. Then the EEMD method is applied to eliminate frequency mixing issues in the signal and obtain the Intrinsic Mode Functions (IMF). Through a simple spectrum analysis, dominant frequencies of IMFs are measured and selected inside the HR and RR frequency range and then classified in groups. To extract the intrinsic cardiac and respiratory information from IMFs, the authors applied a Principal Component Analysis (PCA) to the HR and RR selected groups. The first Principal Component of each group represents the HR and RR information.

In addition to measuring HR and RR using vibration sensors on the bed, other approaches have measured these vital signs in vehicles. For example, Bonde et al. [61] present a continuous heart rate variability (HRV) monitoring in cars based on the estimation of the RR-interval and using a piezoelectric accelerometer. The sensor was attached near the passenger's heart. Due to severe signal interference with vehicle motion, the first stage of target signal extraction was proposed. In this stage, the authors filtered the signal to eliminate high peaks that may correspond to other actions and not the heart movement. A Denoising method was applied to remove engine noise. A continuous wavelet transform [67] was applied to isolate the periodic nature of the heartbeat. To detect the heartbeat, the authors used a peak detection algorithm and a local maxima method. Then, using a sliding window, the distance between the first two peaks is calculated as the RR-interval. The experiments in [61] showed an error of 54ms for RR-interval estimation. Fig. 4 shows four different methodologies utilized in the works that are based on the vital signs estimations on signal processing methods.

Recently, multiple efforts have been made to apply machine learning and deep learning techniques to vibration signals to estimate vital signs. In 2020, Park et al. [36] presented a geophone-based sensing system for extracting electrocardiogram (ECG) patterns using heartbeat vibration through a bed mattress. The signal is first filtered by passing the signal through a bandpass filter to keep frequencies between 5–30 Hz. Then, the data passed on to a Bidirectional Long-Short Term Memory (Bi-LSTM) [68] deep learning model for ECG waveform estimation. The deep learning model architecture in [36] is designed using two-stacked Bi-LSTMs and three fully connected layers. Fig. 5 (adapted from [36]) illustrates the ECG estimation model using Bi-LSTM. The model maps the non-linear relationship between various signal inputs with the corresponding ECG signal. Multiple practical scenarios were presented by the authors to evaluate the model. Comparison between the model output and the ground-truth ECG signals were made to identify peaks from both using the QRS detection algorithm proposed in [69]. Errors between the model and the ground-truth were less than 1.2%.

Other works have focused on estimating breathing states. Choudhary et al. [71] presented a method to assess human respiratory system by identifying degree-of-breathings, such as breathlessness, normal breathing, and long breathing. The input data are SCG signals. The authors extracted 15 statistically significant morphological features from the SCG cycle including heart-rate, beat energy, beat entropy, kurtosis [72], autocorrelation feature [73], IM/IC amplitude [72], maximum spectral amplitude, and beat spectral centroid. Then, a Stacked Autoencoder (SAE) deep learning architecture was employed for identification of different respiratory-effort levels. The method had an overall accuracy of 91.45% in recognizing the breathing stages.

Table 1 shows different vibration-based approaches for heart rate estimation. The vast majority of the approaches (nine papers) utilized pure SP techniques, whereas only one paper involved the use of ML. Table 2 indicates the methods exclusively for respiration extraction. In this case, four papers relied on the use of SP, and two used ML techniques.

2.1.2. Sleep monitoring

Sleep activity is one of the crucial factors for determining the quality of human health. Typically, sleep is studied in clinical environments using dedicated medical devices [74–76]. How-

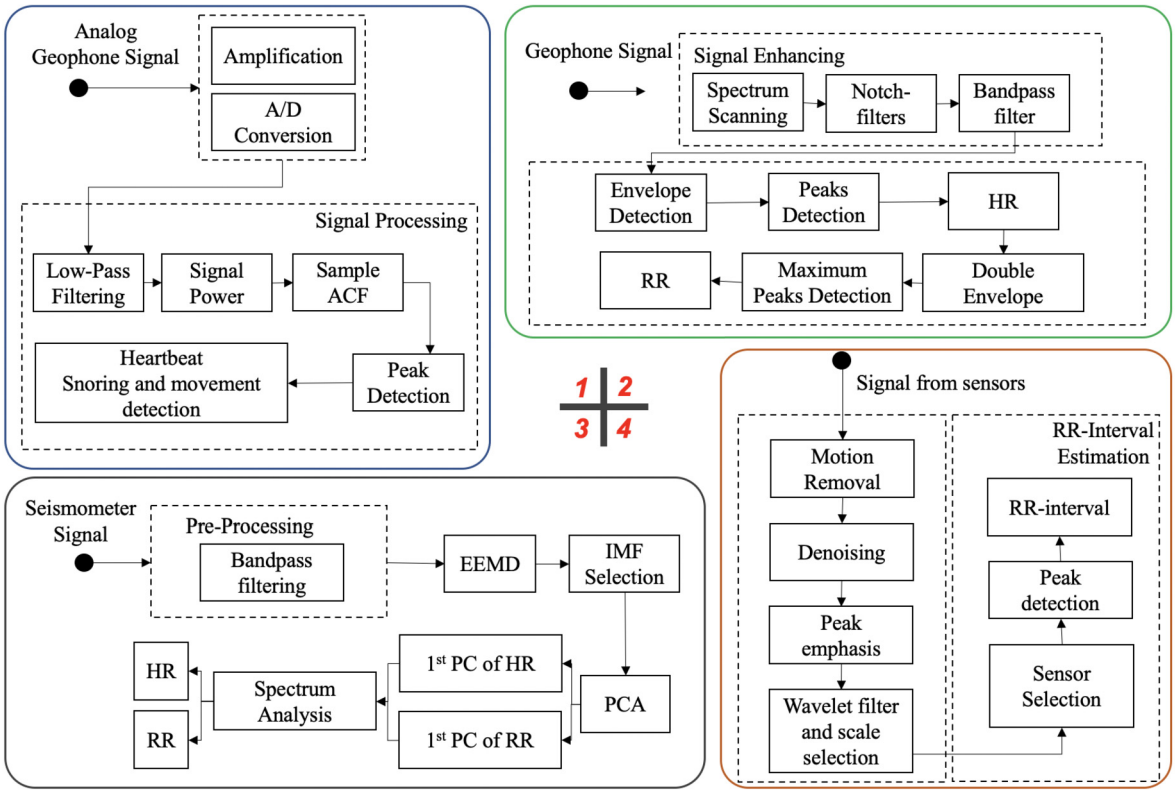

Fig. 4. Signal processing methodologies for HR, RR and RR-interval estimation using vibration sensors. (1) Methodology based on ACF presented in [48]; (2) methodology based on envelope and peaks detection presented in [35]; (3) methodology based on EEDM and IMF presented in [52]; (4) methodology based on peak emphasis and detection presented in [61].

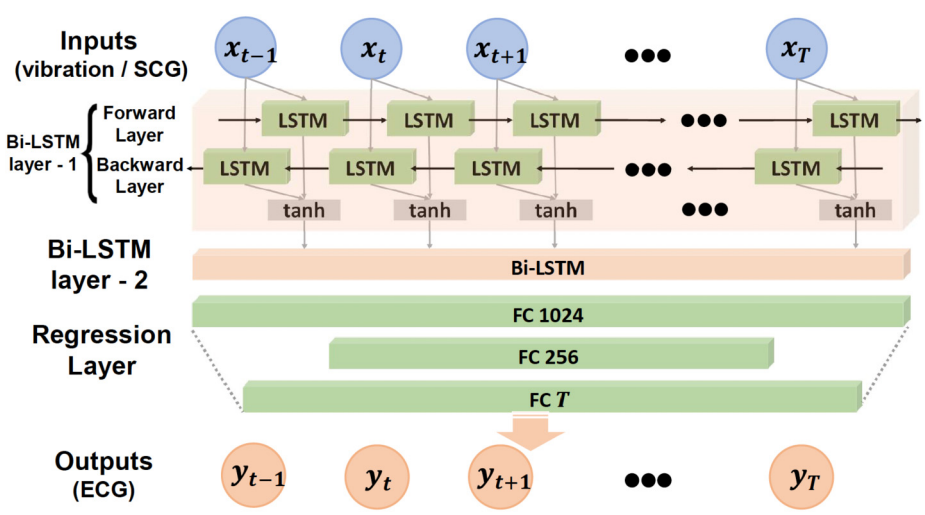

Fig. 5. ECG estimation model using Bi-LSTM presented in [36].

ever, recent technological developments in sensing and data analysis have led to new approaches for sleep monitoring assessment. The new approaches include the monitoring of sleep using wearable and non-wearable devices. Vibration sensors have been used in both types of devices. For example, multiple devices have been used in home-setting scenarios to assess sleep position detection [77–80,77], sleep stage classification [81–83], heart and respiration analysis [84,77], and body temperature [84,85]. The type of devices used for sleep assessment are wide, including smartphones [86–89], microphones [90,91], pressure mats [92–98], pressure bed-sheets [99], eye masks [100], WiFi devices [80], video [101], and bands [102]. In this section, we present the approaches that involve vibration sensor devices and the type of characteristics they measure in order to monitor sleep.

Zhu et al. [103] proposed an automatic system for the long-term monitoring of the quality of sleep. The system uses a piezoelectric transducer placed under a mattress to measure the heart rate, respiration, and the parameters of the body movement at the time of sleep. A sleep efficiency index measurement was estimated using the in-bed detection. The collected data is transmitted to database servers through the Internet. Similarly, Nam et al. [104] proposed a system for quantifying sleep quality. The system was equipped with a three-axis accelerometer and a pressure sensor. The accelerometer was used to measure the sleep pose and ac-

Table 1
Vibration-based approaches for heart rate estimation.

Paper	Sensor and sampling	Data analysis technique	Error	Year
[53]$^{\bullet}_{1}$	Piezoelectric transducer Air-filled bladder	• Normalization, Band-pass filters • Manually count after data collection	±5%	2003
[56]$^{\bullet}_{1}$	Triple-axis accelerometer / 40 Hz	• Low-pass filters and Digital Pulse	Not reported	2011
[48]$^{\bullet}_{1}$	Geophone and amplifier / 10 kHz	• Sample Autocorrelation Function (ACF) • Peak Detection	1.30%	2016
[34,70]$^{\bullet}_{2}$	Geophone / 2.5 kHz	• Short-term Fourier Transform, Spatial signatures • Energy clustering and Binary Masking	1.9 bpm	2017
[39]$^{\bullet}_{1}$	Seismometer / 1 kHz	• Local Maxima Statistics Method	Not reported	2018
[61]$^{\bullet}_{1}$	Piezoelectric accelerometer / 2 kHz	• Denoising, Peak emphasis • Wavelet filter and scale selection	54 ms	2018
[35]$^{\bullet}_{1}$	Geophone / 100 Hz	• Enveloped-based HR method • Peak Detection	±2.41 bpm	2020
[52]$^{\bullet}_{1}$	Seismometer / 100 Hz	• Ensemble Empirical Mode Decomposition (EEMD) • Intrinsic Mode Functions (IMF)	±2.55 bpm	2020
[36]$^{\diamond}_{1}$	SM-24 Geophone / 10 kHz	• Bi-directional Long Short-Term Memory (Bi-LSTM) Deep Learning Model	$< 1.2\%$	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

Table 2
Vibration-based approaches for respiratory rate estimation.

Paper	Sensor and sampling	Data analysis technique	Error	Year
[37]$^{\bullet}_{1}$	Accelerometer / 1 kHz	• Bandpass filter, Segmentation, Peak Detection • Interval computation, Interpolation and re-sampling	∼ 1.1 breaths-pm	2012
[34]$^{\bullet}_{2}$	Geophone / 2.5 kHz	• Spatial Information Extraction • Amplitude Demodulation	∼ 0.38 breaths-pm	2017
[35]$^{\bullet}_{1}$	Geophone / 100 Hz	• Double-enveloped-based method • Peak Detection	±0.89 breaths-pm	2020
[52]$^{\bullet}_{1}$	Seismometer / 100 Hz	• Ensemble Empirical Mode Decomposition (EEMD) • Intrinsic Mode Functions (IMF) / Spectrum Analysis	0.3±1.03 breaths-pm	2020
[71]$^{\diamond}_{1}$	SCG Acquisition Circuitary	• Orthogonal Subspace Projection, Feature Extraction • Stacked Autoencoder-based DNN Model	∼ 5.83%	2020
[28]$^{\diamond}_{2}$	Flexible Low-Frequency Vibration Sensor (FLFV)	• Hardware Design • No Processing Technique reported	Not reported	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

tivity, while the pressure sensor was used to estimate HR and RR. Looking into the accelerometer measurements, this work was based on thresholding methods. The data collected from the system was transmitted over a wireless network of sensors based on ZigBee technology to a portable recording device and to a PC.

In 2019, Hu et al. [105] proposed an approach to identify sleep stages through bed-frame vibrations. The system aimed to distinguish sleep stages between the Rapid Eye Movement (REM) [106] and Non-Rapid Eye Movement (NREM) [107]. Once an event is detected by using a thresholding method, the authors extracted multiple features like average power (AP), the significant peaks with the highest amplitude of the signal, a cumulative variance for a total of 17 features. Then, the authors utilized a scalable machine learning system for tree boosting named XGBoost [108]. XGBoots is a regularized extension of traditional boosting ensemble techniques that belongs to the classification and regression (CART) family [109]. The evaluation was made in the National Children's Hospital. The cross-validation and prediction test achieved an area under curve (AUC) score of 0.84 in recognizing subjects' sleep stages, which is not high but acceptable.

In 2020, Clemente et al. [35] proposed a multi-method mechanism for sleep monitoring. The approach includes multiple parameters (besides HR and RR) to evaluate the sleep. For example, the authors used a Multiple Feature Fusion (MFF) method that combines the Spectral Entropy (SE), the Kurtosis, and the Teager Energy Operator (TEO) of the signal to determine if the person is on the bed or not (On/Off Bed). This work was the first in introducing detection of falls from bed detection. Authors extracted multiple features from the signal including signal amplitude, event duration, amount of sub-events, last 20 peaks information, and power spectral density. Those features feed a Support Vector Machine (SVM) reaching an accuracy of about 97%. In the same work, a thresholding methodology was followed to differentiate movements and changes in the posture of the person on the bed. In the same year, Li et al. [52] also proposed a sleep monitoring approach with a seismometer based on whether the person is on the bed, their movements and posture change. The On/Off Bed estimation was made using an Auto-Correlation Function (ACF) after applying appropriate pre-processing filters. In this same work, sleep posture identification was made using an SVM. The used features included the seven stages of the heart motion cycle recorded by SCG signals [110]. The posture classification accuracy was 92.4%. Table 3 presents a summary of the currently available works on sleep monitoring using vibration sensors; note that for this specific ap-

Table 3
Vibration-based approaches for sleep monitoring.

Paper	Sensor and sampling	Data analysis technique	Error	Year
[103]$^{\bullet}_{1}$	Piezoelectric transducer (PZT)	• Momentum method (movements detection) • Wavelet transform and a soft threshold noise removal method • Adaptive Threshold Method (HR) • Zerocross Point Detection Method (RR) • Sleep efficiency (stable timeOnBed/timeOnfBed)	Not reported	2014
[104]$^{\bullet}_{2}$	Three-axis accelerometer / 60 Hz Pressure sensor	• Bi-directional Recursive Filter • Threshold method (movements and posture detection)	0.076 mean difference against ground truth	2016
[105]$^{\diamond}_{1}$	Geophone / 1000 Hz ADC module	• Feature Extraction • XGBoost [108] machine learning (Sleep Stages)	$\sim$ 0.16%	2019
[35]$^{\diamond}_{1}$	Geophone / 100 Hz	• Enveloped-based method & peak detection (HR) • Double-enveloped-based method & peak detection (RR) • Multiple Feature Fusion Method (On/Off Bed) • Support Vector Machine (Fall from bed) • Thresholding (Movements and posture)	$\pm$2.41 bpm $\pm$0.89 breaths-pm On 0.5% Off 0.27% Fall 3% Mov 2.08% Pos 7.92%	2020
[52]$^{\diamond}_{1}$	Seismometer / 100 Hz	• EEMD and IMF (HR & RR) • ACF method (On/Off Bed) • Support Vector Machine (Posture)	$\sim$ 2.55 bpm (HR) $\sim$ 0.3 bpm (RR) 0.2% 7.6%	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

plication, ML is the lead approach (three papers utilized it versus two SP papers.)

2.1.3. Gait health analysis

In healthcare, the gait pattern of individuals is important to monitor neuromuscular disorders that cause progressive loss of muscle such as Muscular Dystrophy (MD) [111]. There are multiple existing sensor technologies for continuous gait monitoring, such as pressure-based [112], wearable-based [113], and vision-based sensing systems [114]. However, those approaches have limitations; for example, pressure sensors require dense sensor deployment, vision sensors require lines of sight, and wearable sensors require the patient to wear a device for long periods, which makes these approach inadequate for long-term monitoring. Vibration-based systems are a potential alternative for gait analysis that enables the study of the structural vibration to infer the way people walks for medical purposes. The rationality is based on when humans are people is walking each footstep serves as an excitation to the floor to generate a vibration response. By analyzing this response, it is possible to infer the gait and potentially disease-related gait impairments. In this section, we analyze the studies that aim to perform gait analysis for medical purposes based on vibration sensors.

In 2019, Farget et. al [115] introduced a health gait monitoring system through footstep-Induced floor vibrations. The authors decomposed vibration responses to obtain signal peaks that correspond to temporal gait information and leveraged foot dominance to learn a signal amplitude-footstep ground reaction force transfer function. The system has two main modules 1) the footstep detection module that extracts data from an SM-24 geophone sensor and isolates the footsteps by analyzing the impulsive footstep signal and their variance respecting the ambient vibration; 2) a temporal gait parameter estimation module that applies a Continuous Wavelet Transform (CWT) to the isolated footsteps to decompose the signal energy and identify the peaks that correspond to foot interaction with the floor, and 3) a footstep force and gait balance estimation module where the authors train a function mapping the footsteps responses to the ground reaction forces by normalizing the footstep signal. Preliminary results show that temporal gait parameters can be estimated with up to 99% accuracy and gait balance symmetry can be estimated with as low as 10.4% error.

In 2020, Dong et. al [116] presented a vibration-based system that can monitor gait health using footstep-induced floor vibration in non-clinical settings. The authors leveraged a physical-informed approach to extract gait information and reduce structural influences. To separate the mixture of gait information, the authors proposed to convert vibration signals into temporal gait parameters, stability scores, and toe-walking likelihood to quantify physical symptoms that characterize Muscular Dystrophy. An array of geophone was used to measure the vertical velocity of the floor and then it was processed to isolate footsteps traces using a low-pass filter and a Wiener filter [117]. With the footstep extraction, the approach characterize the physical symptoms of MD including 1) slow walking, 2) balance difficulty, and 3) toe-walking gait. Later the authors reduce the effects of the structural vibration by dividing the footsteps into two phases 1) the forced-vibration phase when the gait force is impacting the floor, and 2) the free-vibration phase when the structure is vibrating without excitation forces.

The second phase is then removed. The final step includes the prediction of footsteps from individuals with MD. In this stage, the authors utilized a Support Vector Machine with a Gaussian Radial Basis Function kernel to classify the steps in “healthy” or “Unhealthy” The approach was evaluated with real-world walking experiments at Nationwide Children’s Hospital with thirteen human subjects getting an average accuracy of 96%.

Table 4 presents the approaches for gait health monitoring using vibration sensors. Note that when the footsteps need to be classified as healthy or unhealthy, the approach is required to use an ML technique. More application for monitoring gait in terms of human behavior will be presented in Section 3.

2.2. Single sensors vs sensor networks

In terms of health assessment and monitoring, the vast majority of the works utilize one single vibration sensor for the monitoring process of a single person. As shown in Tables 1, 2, and 3, very few methods incorporate more than two vibration sensors. Some methods for monitoring include more than one [28], but the objective is to monitor multiple activities, not only health. One work that incorporates more than two vibration sensors to estimate RR is the one presented by Jia et al. [34]. The authors used geophones to sense bed vibrations caused by the ballistic force of two occupants.

In such situations, the vibration from both persons are mixed, and a spatial difference between two signal sources (two geophones) is computed for each vibration sensor to extract the two

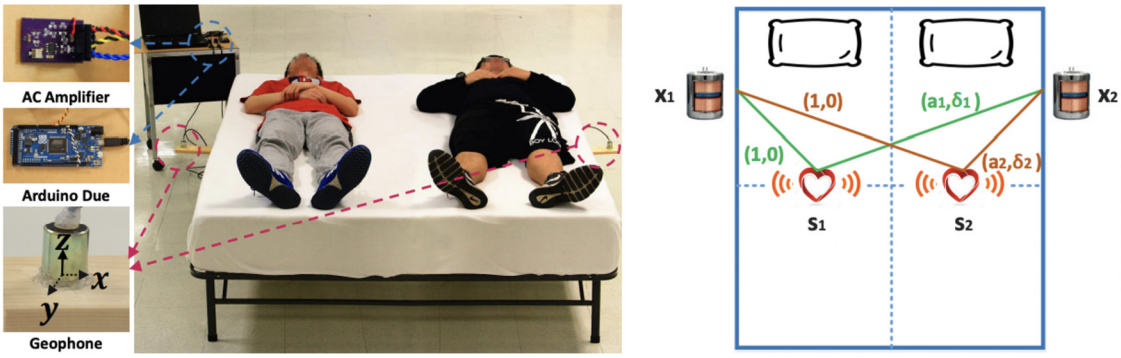

Fig. 6. Experiment setting used in Jia et al. [34] with two sensors and the corresponding attenuation coefficients and time delays used to separate the two persons' heartbeats.

Table 4
Vibration-based approaches for gait health monitoring.

Paper	Sensor	Data analysis technique	Accuracy	Year
[115]$^{\bullet}_{1}$	SM24 Geophone	• Amplification and Anomaly Detection Algorithm • Continuous Wavelet Transform (CWT) • Peak detection • Function mapping	99%	2019
[116]$^{\diamond}_{2}$	Array of Geophones	• Lowpass filter and Wiener Filter • Physical MD symptoms characterization • Support Vector Machine with Gaussian Radial Basis Kernel	96%	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

different heartbeat signals, and then the respiration extraction algorithm deciphers the breathing rate embedded in amplitude fluctuation of the heartbeat signal. The number of geophones used must be the same as the number of persons on the bed. The approach works as follows. First, the authors formulate the heartbeat separation problem by defining the mixed signals [118] and considering one geophone as a reference signal. Then, the relative attenuation and delay coefficients were estimated. The authors apply a low-pass filter to filter out environmental noises, an Short-Term Fourier Transform (STFT) of the two geophone signals, a spatial signature method to estimate the symmetric attenuation and relative delay between the two STFT, an energy clustering method to estimate each frequency bin, and binary masking to identify the peaks that refer to HR. Fig. 6 shows the experiment presented in [34] with two subjects and two geophones (x_1 and x_2) and the corresponding attenuation coefficient from each sensor.

One important detail in [34] is that even though the approach aims for continuous monitoring of HR and RR, the geophones are not forming a sensor network. In other words, the data is manually collected and mixed from the two sensors to deliver the results. This opens a line of research in how to utilize a sensor network of geophones or vibration sensor to estimate more accurately the HR, RR, sleep quality, and other vital signs like blood pressure and oxygen levels.

3. Behavior recognition

Some home monitoring research has tried to understand a broad range of human behaviors such as Activity of Daily Living (ADL) [119,120]. Multiple types of sensors have been used to recognize ADL and human behavior; for example, inertial sensors (accelerometers [121,122], gyroscope [123], magnetometer [124]), physical health sensors (electrocardiogram [125], skin temperature [126], electroencephalograph [127], electromyogram [128], force/pressor sensor [129]), environmental sensors (temperature [121], humidity [130], light sensor [131], barometer [132]), and others like cameras [133], microphones [134], and GPS [135].

The monitoring of human behavior is essential in senior population, as the main goal is to observe and determine sudden changes in behavior patterns. Some of the main activities to recognize include gait changes, eating habits, washing habits, and bedrooms habits. These main activities may provide a guidance to detect anomalies in the behavior. On the another hand, several studies have demonstrated that the behavior and physiological responses of farmed animals provide reliable information about animal health status and welfare [136]. The animal behavior can be measured using different types of sensors and data analysis techniques. Systems based on GPS are among the most popular ones [137–139]. However, other approaches using accelerometers [140], video [141], and wireless sensors [142] have been proposed along with multiple data analysis techniques including k-means classifiers [139], Kalman filter identification [143], and classification trees [144]. Here, we focus on the different approaches that have been proposed to monitor human and animal behavior in the context of vibration sensors.

In this section, we explore the different signal processing and machine learning techniques that have been used to estimate human behavior and ADL (Section 3.1). We also present the different types of sensors and/or sensor networks used on each approach (Section 3.2).

3.1. Data analysis techniques

Similar to health assessment and monitoring, the data analysis techniques for behavior recognition vary depending on the type of the application. Here, we explore relevant works on human behavior (Section 3.1.1) and animal behavior (Section 3.1.2).

3.1.1. Human behavior

Cho et al. [145] presented an approach to model and monitor human behavior in a bedroom using wireless infrared and vibration sensors. In this approach, two vibration sensors were used, one inside the pillow and one by the bedside. The authors defined behavior states and behaviors, such as "behavior for a person standing near a bed to go and sit down the bed," "behavior for

a person sitting on a bed to lie down on the bed," "behavior for a person lying on a bed to toss and turn," and so on. For each stage, multiple features were extracted from the signal by empirically observing the behavior of the signal during the experiments. A feature vector was created, and a state preserving approach was used for recognition with an accuracy of 75.4%. In 2015, Tsukiyama [120] presents an empirical model to determine "normal" behavior in a house depending on water-flow vibration sensors that measure the water utilization in toilets and sinks. The author proposed that depending on the normal water utilization, one can measure if senior people are doing normal activities. The model includes the frequency of urination during nights based on the toilet flush, frequency of water usage in the kitchen, washroom, and bathroom when the resident is inside the house.

Fargert et al. [146] presented in 2017 a monitoring mechanism of hand-washing practices using structural vibration. In this study, the authors used a geophone and an operational amplifier attached to a sink structure. First, the hand-washing activity was isolated from the signal using an anomaly-based detection algorithm. Then, the system used the isolated signal to estimate multiple features like the energy distribution using a Power Spectral Density (PSD) function and the sum across frequency bands centered on the natural frequencies of the sink structure. Finally, the detected hand-washing activity was classified using a support vector machine algorithm. The accuracy of the proposed detection reached 95.4%.

In 2018, Mirshekari et al. [147] presented a structure-adaptive approach for monitoring human gait using floor vibrations. The approach was composed for three modules. The first module, Impulse Detection, monitors the floor vibration signal from the geophone and isolates signals with larger variations as potential footsteps. The second module, Structure-Informed Model Transfer, labels the impulses, finds the low-dimensional latent space from a set of principal components, and predicts sample labels in the target structure with the model. This process allows the frequency representation as a feature for estimating the footstep model. Finally, the Labeled Training model trains a new footstep classification for the target/new structure with the labeled data from module two. The three modules provide the analysis of the human gait. In the same year, Jabal et al. [148] presented a model for human behavior recognition using a wearable accelerometer. The approach includes a signal pre-processing and noise reduction stage utilizing a median filter [149]. Then, the feature representation and extraction was made using a Hierarchical Features Representation Methods. This method consists of extracting statistically dependent features such as magnitude of the signal, minimum and maximum signal features, standard deviation, and signal magnitude area. The classification among different behaviors was made using an optimal margin-based classifier with lesser complexity as linear support vector machine [150]. Results showed that the approach was able to identify different types of behaviors (walking, drinking, climbing stairs, etc) from available public databases.

In 2019, Pan et al. [151] evaluated the recognition of different activities of daily living using two vibration sensors and one electrical sensor. The vibration sensors were two geophones, one located at the counter-top of a kitchen and the other on the floor. The main activities analyzed with the vibration sensors including stove use, kettle use, open/close door, vacuum use, and walking. The authors first performed signal feature extraction and energy normalization. The vibration features included the signal segments of the same time duration over the two surfaces and frequency components concatenation. With those features, the authors applied an SVM with an RBF kernel to ensure high-class separability. Results presented in Table 5 only show the error of the vibration sensor on the counter-top of the kitchen. In 2020 by Xu et al. [152], the authors present *TouchPass*, which utilizes active vibration signals on smartphones to extract only physical features of touching fingers to perform user identification. The approach involves the following steps. First, when the user touches the smartphone screen with the fingers, *TouchPass* collects, calibrates and segments the vibration signal obtained by an International Mathematical Union (IMU) sensor. Based on the segmentation, a Waveled-based feature extraction is performed to extract features in transient-state and steady-state of vibration propagation. A Cepstrum-based feature extraction is also applied to extract steady-state of vibration signals. Using these features, a behavior-irrelevant on-touch user authentication model is proposed. In particular, the approach develops a Siamese network-based method to reconstruct the extracted features to behavior-irrelevant features. Then, a distillation-based model is proposed to train a light-weighted behavior-irrelevant model for user authentication. Multiple evaluations were conducted. The reported accuracy was around 92% for legitimate users authentication, and around 94.5% for spoofer detection.

In 2020, Bonde et al. [153] presented an overlapping office activity classification using IoT devices that measure structural vibration. In this study, multiple overlapping activities in an office were assessed using largely amplified geophone signals. The major activities were classified into two categories. Category one includes activities such as sitting at a desk quiet, talking, or writing. Category two includes active activities such as sit, stand, or walk. The authors also evaluate the overlapping between both categories. The feature extraction was made utilizing a Short Term Fourier Transform (STFT) and summary statistics (maximum, mean, and variance). Then, an activity classification module was proposed. In this module, the authors used two stages of support vector machines. Finally, they combined the outputs of the two SVM. Results showed that the accuracy was 97% for category one, 90% for category two, and the overlapping of both categories as 90%. In the same year, Akiyama et al. [154] presented a methodology to estimate walking direction using vibration sensors. In this approach, two piezo elements were used, and they were assembled into a hardware system that also includes amplifiers and ADC/DAC converters. The approach for walking direction consisted of three steps. First, a pre-processing stage that includes taking the signal of the two vibration sensors, applying Short-Term Fourier Transform (STFT), and obtaining the sum of the power spectrum of all the frequencies on the same time axis, and calculating the difference of the signals. Second, the authors applied a Linear Discriminant Analysis (LDA) to the difference data to extract and classify features used for machine learning. A data dimensionality reduction was also applied to reduce the number of dimensions of two by LDA. Finally, the authors applied multiple machine learning techniques (KNN, Logistic regression, SVM liner, SVM RBF, Decision Tres, and Random Forest) to verify which one presented the best results. A 90% of the accuracy of walking direction was obtaining with KNN and SVM liner. In 2020, Moreu et al. [155] presented a framework for quantifying dance quality and coordination utilizing floor accelerometers. In this study, the authors placed two sensors on the floor with multiple dancers around. They first estimated the Harmony index that captures the standard deviation in harmony by each dancer relative to the mean dance, assuming that is an expected harmony. This was accomplished by looking into the peaks of the signal. Then the authors estimated the Coordination index that captures the lack of symmetry of the vibration of one dance jump. This was accomplished by comparing the temporal separation between the highest peak acceleration and the centroid of all the acceleration for each dance step. For comparison purposes, the authors also quantify a Visual index that indicates the dance quality based on an expert observation. The accuracy of the dance quality against visual observation was around 90%. Table 5 presents a summary of the available works on human behavior recognition using vibration sensors. The vast majority of the studied papers on human behav-

Table 5
Vibration-based approaches for human behavior recognition.

Paper	Sensor and sampling	Data analysis technique	Recognized behavior	Error	Year
[145]$^{\diamond}_{2}$	Two piezo vibration sensors / 60 Hz One Passive Infrared sensor	• Feature Vector • Finite State Machine (FSM)	Activities on bedroom	24.6%	2012
[120]$^{\bullet}_{1}$	Water-flow vibration sensor / 10 kHz RFID tags	• Empirical model of normal water usage	Toilet flush Washroom sink usage Kitchen sink usage	Not reported	2015
[146]$^{\diamond}_{1}$	Geophone Operational amplifier	• Frequency-based feature extraction • Support Vector Machine	Washing hands	4.6%	2017
[147]$^{\diamond}_{1}$	Geophone Amplifier	• Feature extraction and Labeling • Support Vector Machine	Human Gait	3%-14%	2018
[148]$^{\diamond}_{1}$	Accelerometer	• Pre-processing and noise reduction • Hierarchical Features Representation • Support Vector Machine	Climb stairs Drink glass Get up bed Pour water Sit down chair Stand up chair Walk	5.89% 11.77% 14.71% 0% 18.19% 17.65% 17.65%	2018
[151]$^{\diamond}_{2}$	SM-24 Geophone Electrical sensor	• Feature Extraction and Normalization • Classification with SVM • Equal-Weight Method for both types of sensors	Put on Stove Use Kettle Open/Close Door Use Vacuum Walking	6.9% 12.3% 8.7% 2.0% 8.6%	2019
[152]$^{\diamond}_{1}$	Smartphone IMU Sensor	• Wavelet-based & Cepstrum-based features • Siamese Network-based Feature Reconstruction • Knowledge Distillation-based Classifier Training	User identification based-on user finger movements while touching screen	$\sim 5\% - 8\%$	2020
[153]$^{\diamond}_{2}$	Geophones	• STFT and summary statistics • Two Parallel Supervise Classifier (SVM) • Combination of the classifiers	Office activity Cat 1: Quiet,talk,write Cat 2: Sit, Stand, Walk	 3% 10%	2020
[154]$^{\diamond}_{2}$	Vibration Piezo Element	• STFT / Difference of signals • Linear Discriminant Analysis (LDA) • Dimensionality reduction / KNN SVM	Walking direction	10%	2020
[155]$^{\bullet}_{2}$	Accelerometer / 100 Hz	• Peak Selection • Harmony Index (standard deviation in harmony) • Coordination Index (Lack of vibration's symmetry) • Visual Index (Observation)	Dance Quality	11%	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

ior rely on ML techniques (eight out of ten), which means that ML is the significant trend in this kind of application.

3.1.2. Animal behavior

Geophones and vibration sensors also have been used for understanding animal behavior. Accelerometers, for example, have played an important role in inferring animal activities from multiple species like horses [160], elephants [159], koalas [157] and dogs [161]. Accelerometers also have been use to collect behavioral data of elks [162] and fur seals [163]. Accelerometers have been also used in chickens, ducks, and quail for determining the cease of body movements after euthanasia [164,165].

One work of classifying chicken's behavior with accelerometers was presented by Banerjee et al. [156] in 2012. In this study, a light accelerometer was placed inside a casing and mounted on a hen's back with a nylon harness as shown in Fig. 7(1). Data from different activities were collected. The six extracted behavior activities include sit/sleep, stand, walk/run, feed, drink, and dust-bathe. To classify these activities, the authors first extract some features from the signal. The features were the entropy and the mean. Then, the authors evaluate multiple classifiers, including Decision Trees and Naive Bayes Tress, but finally, decide to use Neural Networks as it exhibited the biggest accuracy. For training, 50% of the data was used, and the other 50% was used for testing. The neural network was composed of two layers. In the first layer, the classification was made using three states: static activities, dynamic activities, and resource use. Then, the second layer was composed of the six aforementioned behavior activities.

In animal behavior, the majority of work has been done using accelerometers. However, a good attempt at analyzing animal behavior was made by Bonde et al. [158] in 2018. That was the first attempt to analyze farms using structural vibration from the pigs. The same group, later in 2020, presented an infrastructure for collecting data from multiple geophones deployed in a remote pig farm [153]. Even though the work presents only the data collection infrastructure, the authors successfully integrated sensors and 4G to remotely obtain the data. Table 6 presents a summary of the available works on animal behavior recognition using vibration sensors. Contrary to the human behavior approaches, SP techniques are most commonly used for animal behavior recognition (five out of six studied papers.)

3.2. Single sensors vs sensor networks

In terms of human behavior, the vibration approaches have demonstrated that can obtain multiple behavior recognition using only one sensor [120,146–148,152]. However, the use of multiple vibration sensors is useful to determine overlapping behaviors. The combination of the two or more sensor signals provides more robust information about human behaviors. That is the case of the work in [153], where multiple geophone signals were used to discriminate among different behaviors inside an office. Regarding an-

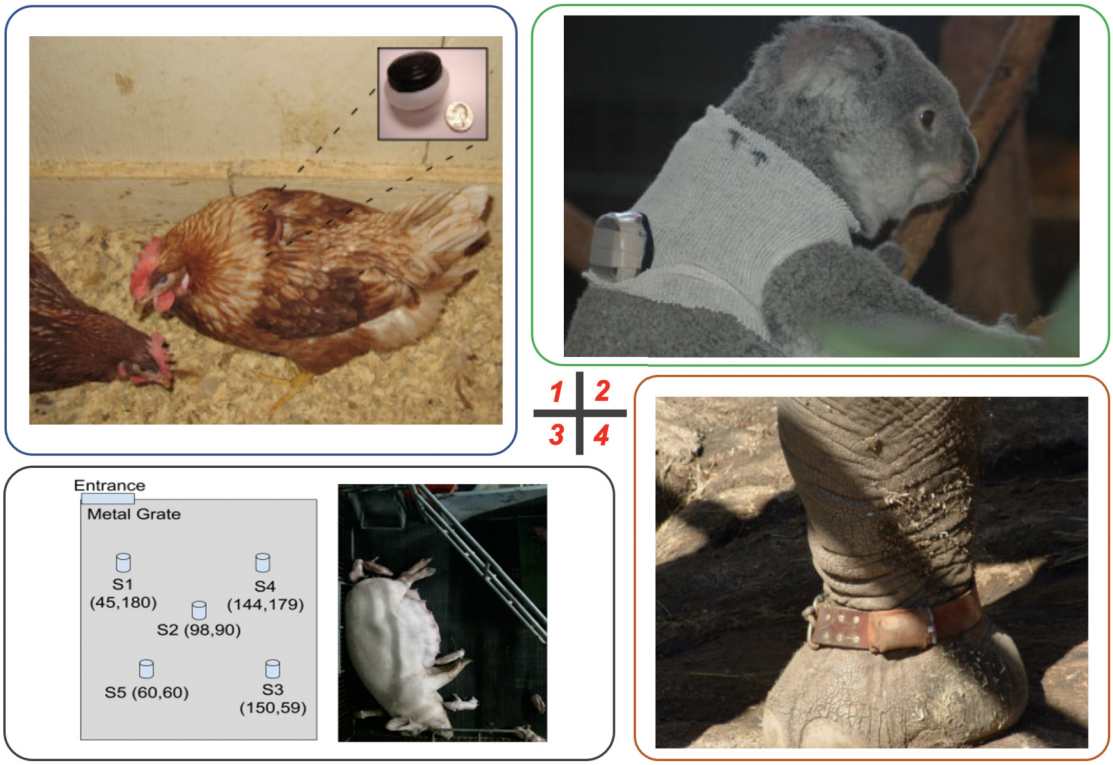

Fig. 7. Wearable and non-wearable vibration sensor for animal behavior recognition. (1) Chicken behavior [156]; (2) Koala estrus monitoring [157]; (3) Pig activity and location of geophones [158]; (4) Elephant walking distance measurement [159].

Table 6
Vibration-based approaches for animal behavior recognition.

Paper	Sensor and sampling	Data analysis technique	Recognized behavior	Animal	Error	Year
[161]$^{\bullet}_{2}$	Accelerometer / 32 Hz ADC	• Down sampling / Minimum distance moved estimation • Thresholding methodology / Correlation with video	Activity level	Dog	$\sim 7-29\%$	2007
[157]$^{\bullet}_{1}$	GT1M Accelerometer 150 Hz	• Empirical active and inactive status determination • Correlation coefficients with endocrine state	Monitoring estrus	Koala	Not reported	2009
[159]$^{\bullet}_{1}$	GT1M Accelerometer 60 Hz	• Empirical footstep distance measure • Correlation coefficients with GPS	Walking distance	Elephant	$\sim 31-53\%$	2011
[163]$^{\bullet}_{2}$	Accelerometer 8 Hz-32 Hz	• Visual time-series data analysis	Mandible open behavior	Fur Seal	$\sim < 5\%$	2011
[156]$^{\diamond}_{1}$	MEMS accelerometer	• Feature extraction: Entropy and Mean • Neural Network Classifier	Sit/Sleep Stand Walk/Run Feed Dust-bathe Drink	Chicken	12.90% 29.19% 0.02% 23.31% 0.08% 0.1%	2012
[166]$^{\bullet}_{2}$	Geoscope-178 & 179	• Data collection: Anomaly detection (time domain) • Anomaly detection (frequency domain)	Monitoring (just data collection)	Pig	N/A	2019

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

imal behavior, the majority of the works have been done using accelerometers. Some studies have used more than one accelerometer to recognized the animal behavior [161,163]. But those sensors do not involve the creation of a sensor network for sharing data. Until, 2019, when [166] presented their data collection approach for pig farms, a sensor network was proposed. This work introduces the use of anomaly detection algorithms in the time and frequency domain to ensure the correct and continuous streams of sensor data. The system also introduces a method for system fault tolerance. This kind of approach can set a base for future work in which multiple sensors can independently interact with each other without the use of servers to recognize behavior in humans and animals. This is a promising and yet unexplored research branch.

4. Occupancy information inference

An increasing number of solutions use occupancy information for many scenarios such as asset tracking, estimate number of people in a place, logistics, security, etc. Since most human activities at home or office are attached to rooms and to interactions with equipment, an occupancy information system must be first able to describe the position of the subjects relative to rooms and tools [167]. Occupancy estimation applications are mainly fo-

cused on locating subjects or people inside determined areas. To achieve occupancy estimation and detection, many types of sensors have been used. For example, passive infrared (PIR) sensors have detected the presence and absence of occupants in an office [168–171]; cameras also have been used to obtain the number of occupants in a room [172,173]; even CO_2 and environmental sensors have obtained a rough estimation of occupancy [174–177]. Besides occupancy, person and multi-person indoor location is a hot topic that has been widely explored for activity characterization. Many approaches utilize wearable sensors and are based on Local Positioning Systems (LPS) [178] or Pedestrian Dead Reckoning (PDR) [179–183]. Other location solutions do not require the user to carry any devices. These approaches rely on tomographic solutions [184], pressure sensors [185], binary sensors [186], etc. Tracking is also another important information that helps to follow the human activities inside a building or room. Although GPS can obtain the location outdoors with room-level accuracy, it performs poorly indoors because the received signal power decreases with the lack of line of sight. Then, other types of sensors have been used. For example, pedestrian tracking have been obtained using WiFi signals [187], cameras [188], drones [189], and many more.

Regarding vibration sensors, some studies have been done for the aforementioned occupancy information inference. The use of multiple vibration sensors is typical in this type of application. However, the vibration sensors have been more used for outdoor underground object/earthquakes locations [190–193] to discussed in Section 6. Here, we are going to discuss the different approaches for occupancy information inference with vibration sensors focusing on three main categories: occupancy itself, localization, and tracking of people.

In this section, we explore the different signal processing and machine learning techniques that have been used for occupancy information inference (Section 4.1). We also present the different types of sensors and/or sensor networks used on each approach (Section 4.2).

4.1. Data analysis techniques

Similar to behavior recognition, the data analysis techniques for occupancy information inference vary depending on the type of application. Here, we explore relevant works on occupancy estimation (Section 4.1.1), occupant localization (Section 4.1.2) and pedestrian and surface tracking (Section 4.1.3).

4.1.1. Occupancy estimation

The current vibration-based approaches for occupancy estimation use different data analysis techniques based on statistic signal analysis [194–196], matched filtering [197], neural networks [198], and support vector machines [199]. Here, we present the most recent ones that cover the spectrum of different data analysis techniques. One of the first approaches that estimates occupancy using vibration sensors was presented by Pan et al. [200] in 2014. This work uses a data collection board based on an arm-based flash MCU and SM-21 Geophone with sensitivity of 28.8 V/m/s. This was a low-cost analog sensor. The system first detects footsteps using an anomaly detection technique that identifies signal energy changes from the ambient noise model. It then localizes footsteps based on signal energy variations and known sensor locations. Finally, structural features and a sequence of localized footstep events are used to track and count occupants. The system is shown to achieve 99.55% event detection accuracy, located the footsteps within three feet, and obtained an occupancy count accuracy of 85% in two different buildings.

An occupant traffic monitoring system was proposed later in 2016 by the same group [201]. In this study, the authors aim to address the issue of distinguishing multiple simultaneous walkers. Its vibration sensing unit consisted of a geophone, amplifiers and filters, and analog-to-digital converters (ADCs). The acquired signals are analyzed, and extracted features are passed to K-Nearest Neighbor (KNN) algorithm to obtain the occupant traffic information. With collected occupant footstep-induced structural vibrations, selected features are evaluated by comparing them through different categories. Tests on both impact loading and human walking in a commercial building are conducted. The evaluation results showed that the occupant number detection for one to four people walking in the same direction achieves less than 0.2 people mean estimation error for each case.

Another occupant detection method through step-induced structural vibration was developed by Lam et al. [199] by incorporating structural characteristics. In the proposed platform, a geophone (SM-24) is used with a DAQ assistant to collect vibration signals. The design has an offline component which characterizes the structure and an online component which performs footstep detection incorporating the structure characteristics. The proposed algorithm first identifies dominant frequencies and then set the threshold using wavelet analysis on the signals. The dominant frequencies and the thresholds are passed to occupant footstep detection based on one-class SVM (OSVM). The platform was validated in both a Carnegie Mellon University building and Vincentian Nursing Home. The average of precision rate reached 0.87 and the average recall rate was 0.93. The results showed up to 50% improvement over the traditional threshold method, which also translates to up to 4X reduction in detection error.

In 2017, Reuland et al. [202] presented an occupant detection method using multiple Roctest Actimon-X1 sensors underneath the slab that measure accelerations with a maximum sampling rate of 2000 Hz. The signal processing method used is Error-Domain Model Falsification that was proposed by Goulet et al. [208] and extended in this study for human localization using acceleration data. The approach was able to identify occupants and estimate the area in which that specific occupant was located. Zhan et al. [203] presented an occupant activity level estimation using geophones. In this study, a sparse sensor configuration was deployed on the floor to monitor activity levels by estimating occupancy. The vibration signal from the floor is amplified, digitized, and processed to ensure noise filtering and occupant vibration recognition. In order to estimate the activity level, a collaborative threshold selection, and event detection was proposed. The threshold value was adapted according to the “normal” signal level between 12 am and 5 am, assuming that no occupancy is detected at that time. The proposed approach obtained a high correlation with access control records that were considered ground truth in both workdays and weekends. In 2019, Drira et al. [204] presented an occupant detection strategy based on a classification method to distinguish footsteps from other events. A SM-24 geophone with a sampling rate of 1 kHz was used. The measured signal is firstly decomposed using a continuous wavelet transform (CWT) and then, the event detection is based on computing the standard deviation of a moving window over several frequency components of the measurements. The authors later used a binary SVM to classify the events that corresponds to footsteps.

In 2019, Pan et al. [205] presented an area occupancy counting using sparse structural vibration sensing. In this study, multiple geophone sensors were deployed to the floor and event detection was used to estimate occupancy. The work addressed various challenges including the reduction in amplitude when the person walks in a room and the signal is obstructed by walls and the complexity of signal mixture when multiple people walk simultaneously in the sensing range. The authors proposed estimation of the traffic count by characterizing the signal mixture for different traffic conditions and utilizing the traffic counts and

Table 7
Vibration-based approaches for occupancy estimation.

Paper	Sensor/sampling	Data analysis technique	Type	Error	Year
[200]$^{\bullet}_{2}$	Geophone / 2 kHz	• Feature extraction / Sum Features/ Noise Modeling update • Tracking based on Velocity Change Event (VE)	Event Detection Occupancy counting	0.45% 15%	2014
[201]$^{\diamond}_{2}$	Geophone / 1 kHz	• Feature extraction based on cross-correlation and entropy • K-Nearest Neighbor (KNN) Classifier	Occupant Number	Mean 0.2	2016
[199]$^{\diamond}_{2}$	Geophone	• Continuous Wavelet Transform • One-Class SVM	Occupancy 1 person Occupancy 2 people Occupancy 3 people Occupancy 4 people	16.67% 33.33% 66.67% 8.33%	2016
[202]$^{\bullet}_{2}$	Roctest Actimon-X1 (Accelerometer/ 2 kHz)	• Gaussian white noise process / Bandpass & Butterworth filters • Error-domain Model Falsification	Occupant detection Possible Location	~ 5 meters	2017
[203]$^{\bullet}_{2}$	Geophone	• Collaborative threshold selection • Threshold-based event detection / Activity count	Occupancy activity level	$\sim 13-23\%$	2018
[204]$^{\bullet}_{2}$	Geophone / 1 kHz	• CWT and signal segmentation / Time difference • Binary-SVM classifier	Occupant detection	Mean 7.5%	2019
[205]$^{\bullet}_{2}$	Geophone	• Event detection through anomaly detection • Event segmentation through peak analysis • Event Identification through window energy array • Counting using signal features	Occupant detection Traffic estimation Occupant activity	0.45% mean 0.2 mean 0.2	2019
[206]$^{\diamond}_{2}$	Geophone	• Feature Extraction (spectrum ratios) • Support Vector Machine	Occupant Presence	2.3%	2020
[207]$^{\diamond}_{2}$	Geophone / 25 kHz	• Feature-based transductive transfer learning • Structure-based data projection	Occupant Detection	$< 2\%$	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

heuristic about structural properties and human walking to tract the occupancy. In the traffic counting, multiple features were extracted from the processed signal; for example, the normalized cross-correlation between spatial-different signals, the normalized cross-correlation between temporal difference signals, the signal duration, and the signal entropy. High accuracy was achieved with the method with less than 0.2 people mean for traffic estimation and occupant tracking. Later, in 2020, Mirshekari et al. [207] presented a step-level occupant detection across different structures using footstep-induced floor vibration. In this study, the authors presented an innovative transfer learning methodology to identify occupants. They used a Feature-based Transductive Transfer Learning approach. This kind of approach aims to find a feature space in which the distributions of data in source and target share similarities. The authors addressed multiple challenges; for example, they tested the approach in multiple different structures; the structural effects on the vibration responses were characterized to develop a physics-driven model transfer approach that projects the data into a new feature space with less structural effect. The occupant detection was evaluated in various structures with different structural materials and characteristics. This approach, is one of the most innovative works, as is the first one to introduce the concept of transfer learning for occupant estimation using structural vibration.

Table 7 presents a summary of the most recent works on occupancy estimation using vibration sensors. Note that in this kind of application, half of the approaches rely exclusively on SP techniques and half of them on ML.

4.1.2. Occupant localization

As stated in [209], although source localization is a well-developed topic, the methods based on vibration are primarily focused on seismology and damage detection. In in-door environments, locating pedestrians is beneficial for multiple applications, and some of them are already shown in this paper. However, vibration-based localization in buildings and homes is a challenging task due to vibration signal effects like dispersion, reflections, heterogeneity, and material discontinuity. Multiple applications have been developed using footstep vibration and time difference of arrival (TDoA) to locate indoor pedestrians as shown in the works of Mirshekari et al. [210,211] (Fig. 8(1) and 8(3) respectively). However, TDoA presumed wave propagation in ideal scenarios and environments. In the real world, the interaction between the building's structure and the footstep vibration is more complex due to wave distortions. New methodologies have been proposed by researchers such as Choudhary et al. [212] (Fig. 8(2)). In this section, we present the recent research in indoor localization using structural vibration in both, traditional TDoA approaches and new models.

One of the first studies in indoor localization using vibration sensors was presented by Bahroun et al. [213]. The authors introduced the concept of *perceived propagation velocity* which decreases when the source-sensor distance increases. The findings of the model led the authors to propose a new localization algorithm that is adapted to dispersive mediums, using only the sign of the measured TDoA (SO-TDoA). The SO-TDoA algorithm consists of region localization instead of an accurate location. Another approach presented by Schloemann et al. [214] utilized the difference between Time of Arrival (TOA) and TDoA of sixteen sensors placed under the building floor; however, in this study, the event was produced by impacting the floor with a hammer.

The same philosophy of using TDoA was presented on large scale by Poston et al. [215]. In this study, the authors placed 240 PCB accelerometers on the structural ceiling at a Virginia Tech building. The approach first attempted to detect the footstep of a person and then localize the detected footstep when possible. To detect footsteps, the authors analyzed the signal to identify the peaks corresponding to a footstep. To localize the footstep, the TDoA between sensors was used. Then, in 2016, the same group presented an improvement of the TDoA methodology for localization [216]. In this study, the authors proposed to use a preprocessing of the signal that consists of a matched filter detector to maximize the signal-to-noise ratio (SNR) and an Additive White Gaussian Noise (AWGN) method. The conventional TDoA processing of matched filter outputs provided sub-meter accuracy. How-

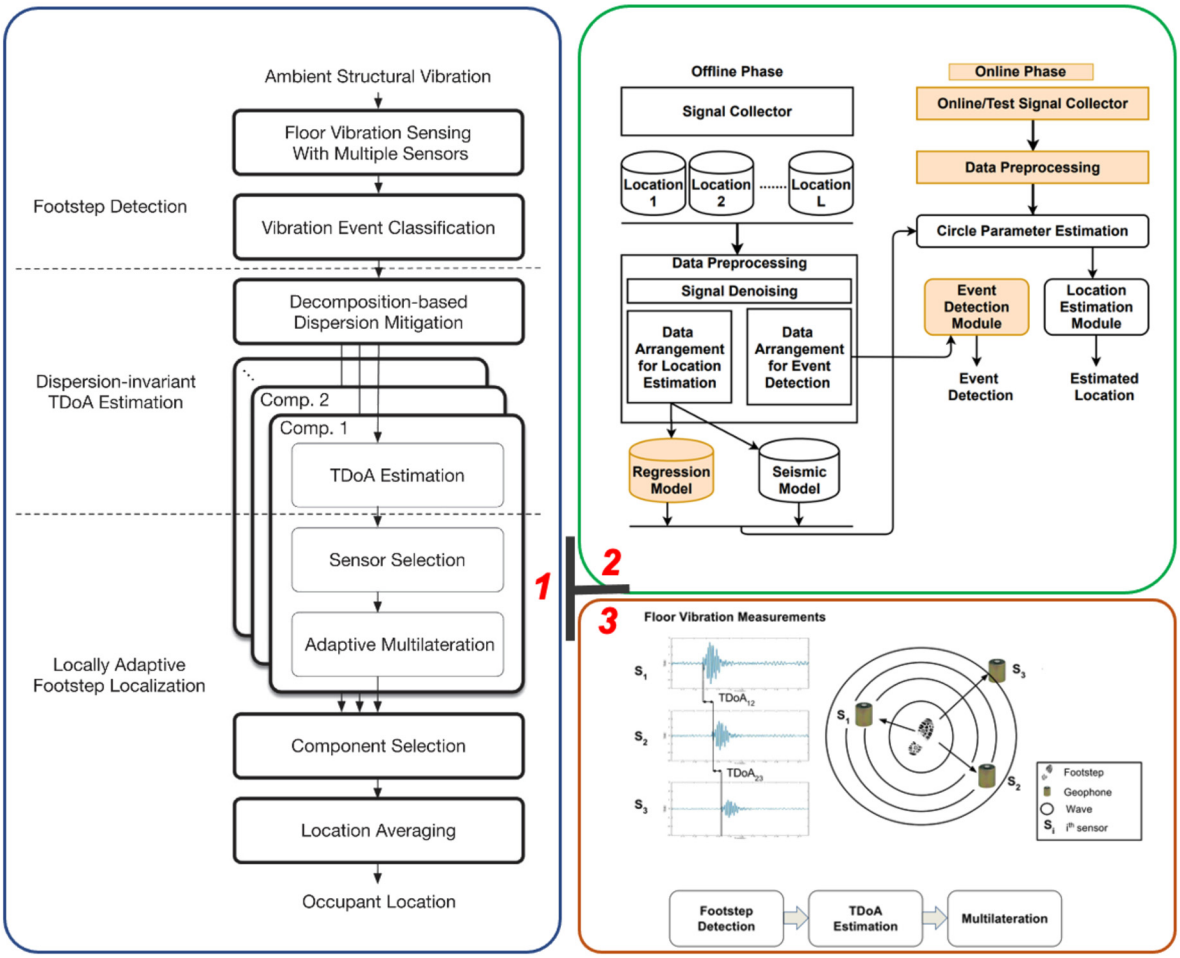

Fig. 8. Pedestrian localization methods based on induced foot-step vibration. (1) Occupant localization approach proposed in [210]; (2) Framework for seismic sensor-based event detection and localization proposed in [212]; (3) Footstep localization method proposed in [211].

ever, this method became unreliable when conducting localization over the full span of a building floor. For that reason, Poston [217] proposed an approach to identify important types of footstep-to-sensor interactions and a more sophisticated TDoA technique. In this case, the author utilized a bank of matched filters to identify two different forms of footsteps. To improve the TOA, the author adapted a seismology phase picking technique to footsteps based on the Akaike Information Criterion (AIC) [218]. Then, the TDoA is estimated by also considering the set of propagation speeds over the physically plausible range.

In the same year 2016, Mirshekari et al. [211] introduce the use of the concept of multilateration in footsteps localization. The approach consisted of three steps; first, the footstep is detected using a thresholding method base impulse-like-excitation [199]; then, a TDoA estimation using time-frequency representations of the signal to extract the high energy peaks used as peak-based TDoA; finally, the footstep localization is estimated using multilateration because the foot strike is unknown and it can be leveraged the TDoAs of the signal to localize the source [219].

Mirshekari et al. [210] later proposed an occupant localization methodology using footstep vibrations based on TDoA, but, in this case, the authors considered the vibration wave propagation in the floor and the floor heterogeneity. In this approach, the footstep detection is accomplished by conducting a chi-squared hypothesis test. Then, the authors proposed a Dispersion-invariant TDoA estimation that uses signal decomposition and then estimates the TDoAs for different components. To estimate the TDoAs between different pairs of sensors for every scale components, the authors used a threshold-based method. Finally, the footstep localization is achieved using a Locally Adaptive method that selects a subset of sensors that are closer to the footstep to further reduce signal distortion effects and estimate component-level footstep localization using an adaptive multilateration approach. The whole approach is described in Fig. 8(1).

One of the first approaches to introduce machine learning techniques for footstep detection and later localization was Clemente et al. [220]. The authors first extracted different features from the vibration signal produced by footsteps and other events; those included time (event duration, standard deviation, entropy, peaks, etc) and frequency domain (spectra, centroid, peaks) features. Then a support vector machine was utilized to classify the events between footsteps, fall downs, etc. Once the event is classified as a footstep, the authors used a real-time TDoA in which the sensors collaborate with each other to estimate the TDoA. In order to improve the TDoA, the authors utilize the floor velocities (obtained after calibration) to eliminate the TDoA assumption of constant speed. The authors also used a Maximum Likelihood estimator to calculate the position of the vector that maximizes the likelihood function. This was the first work to introduce collaboration between sensors for estimating localization. The approach reached an error of 0.47 m. Later, the same group presented a work locate footsteps [221] based on the same philosophy of floor velocity calibration, but instead of using traditional TDoA, the authors proposed a method called Angle-constrained Time Difference of Arrivals (ATDOA), which is an optimization method to estimate

Table 8
Vibration-based approaches for localization estimation.

Paper	Sensor/sampling	Data analysis technique	Error-in-distance	Year
[213]$^{\bullet}_{2}$	Accelerometers	• Perceived propagation velocity of footsteps on floor • SO-TODA algorithm	< 1.5 m	2014
[214]$^{\bullet}_{2}$	PCB Shear Accelerometers	• Difference between Time-of Arrival (TOA) and Time-Difference-of-Arrival (TDoA)	1.14 m	2015
[215]$^{\bullet}_{2}$	PCB Accelerometers 15 kHz	• Footstep detection: Peak Detection • Footstep localization: Time-Difference-of-Arrival (TDoA)	0.22-1.5 m	2015
[216]$^{\bullet}_{2}$	PCB Accelerometers	• Pre-processing: Matched filter detector & AWGN • Reliable TOA measures to form candidate region locations • Indicator function to refine candidate locations	0.1-0.2 m	2016
[217]$^{\bullet}_{2}$	PCB Accelerometers	• Matched filter bank • AIC adaptation from phase picking	0.6-0.8 m	2016
[211]$^{\bullet}_{2}$	Geophones	• Footstep detection: Thresholding method • Peak-based TDoA and Multilateration	0.41 m	2016
[210]$^{\bullet}_{2}$	Geophones	• Threshold-based method for footstep detection mitigation • Dispersion-invariant TDoA Estimation • Locally Adaptive Footstep Localization	0.18-0.34 m	2018
[220]$^{\diamond}_{2}$	Geophones 1 kHz	• Footstep detection: Support Vector Machine • Real-time TDoA and Maximum Likelihood	0.47 m	2020
[221]$^{\bullet}_{2}$	Geophone 1 kHz	• Footstep detection: STA/LTA method • Angle-constrained Time Difference of Arrivals (ATDOA)	0.27 m	2020
[212]$^{\diamond}_{2}$	SM-24 Geophones 10 Hz	• Footstep detection: Decision Tree Classifier • Localization: NLRM or SPM	1.37 m	2020

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

two-dimensional location vector. In this case, every single node determines the footstep event arrival time and direction angle.

In 2020, Choudhary et al. [212] moved the location spectrum to outdoors using vibration signals. The idea of the approach was to use multiple seismic sensors and fuse the information to detect and localize a target in an outdoor environment. The whole approach is presented in Fig. 8(2). After data de-noising, the authors proposed an event detection module using a decision tree classifier to solve the binary problem of presence or absence of a target in area A. Then, the authors proposed a localization estimation module that uses either a Non-linear Regression Method (NLRM) or a Seismic Property based Method (SPM). Results are promising considering that the experiments were performed in outside environment.

Table 8 presents a summary of the recent studies on occupant and footstep localization using vibration sensors. The vast majority of the studied papers utilize purely SP techniques for occupant localization (eight out of ten papers) as they use methods that rely on triangulation of the signals.

4.1.3. Pedestrian and surface tracking

Besides localization, tracking is another important characterization that enables multiple indoor and outdoor applications. Tracking objects can be pedestrian tracking, car tracking, surface tracking for enabling movement tracking, etc. The value of this tracking is tremendous. For example, tracking pedestrians in the monitoring scene can bring business value, and tracking of movements on a surface can lead to pattern recognition and smart home applications. The tracking of pedestrians and objects is not new and has been accomplished using a wide variety of sensor such as cameras [222,223], mobile phones [224,225], WiFi devices [226–228], inertial sensors [179,229,230], wearable sensors [231,179], and more. In terms of data analysis techniques, tracking has been done using signal processing [232,233] and machine learning methods [234–238]. In this section, we study the multiple techniques that have been used for object tracking based on vibration sensors.

In 2016, Pan et al. [239] proposed a multiple pedestrian tracking using vibration sensors. The sensing module samples at 20 kHz with all sensors wirelessly synchronized to the order of microseconds. Each sensor consists of a geophone to detect structural vibration. The footstep-induced signals are first extracted from the vibration signals based on a Gaussian noise model from the noise signal to detect Step Events. The initial region of step signals is identified from the signal segments that contain overlapping step signals, which are used to localize each step leveraging Time Difference of Arrival (TDoA) based localization. The experiments are conducted in an office setting and the proposed system achieved less than 0.4 m of error in both one and two persons stepping conditions. Later, in 2017, the same group presents an on-surface human interaction (tap & swipe) tracking system with vibration sensing [240]. In the design, oscilloscopes are adopted to detect vibrations caused by surface particles moving perpendicular to the target surface. After vibration sensing, interaction identification is performed to identify each tap or swipe. The interaction detection is conducted through anomaly detection. The system identifies an event to be a swipe if the segments above the threshold last over one second. If a swipe is detected after the initial tap, the system conducts tap localization. In tap localization, wavelet-based decomposition is used for band selection and filtering for taps. To localize and track the interaction based on event signals, the proposed system calculates the TDoA of event signals detected at different sensors. Localization is then performed by using multilateration with the pairwise TDoA values from different sensors. In the final swipe tracking module, it outputs the estimated trajectory of a given swipe signal. The evaluation uses metrics such as tap and swipe errors on different materials and varying surface/sensing area sizes. Experimental results show that the proposed system achieves up to 6X decrease in localization error for taps and 3X reduction in length estimation error for swipes compared to other benchmarks without considering wave properties.

In 2017, Poston et al. [241] introduced a framework for occupancy tracking using footstep vibrations. The approach was based

Table 9
Vibration-based approaches for pedestrian/object tracking.

Paper	Sensor/sampling	Data analysis technique	Tracking type	Error	Year
[239]$^{\bullet}_{2}$	Geophone 20 kHz	• Event Detection: Gaussian noise model • Tracking: TDoA, multilateration and particle filters	Multiple pedestrians	0.34-0.39 m	2016
[240]$^{\bullet}_{2}$	Oscilloscope 25 kHz	• Tap localization: TDoA & multilateration • Tracking: Linear fit on the detected locations • Tracking: Distance traveled from farthest points	Tap/Surface	< 0.4 m	2017
[241]$^{\bullet}_{2}$	352B Accelerometers 32 kHz	• Detection: Chi-Square Function / Threshold • Tracking: ThrellisForward and TrellisTraceback algorithms	Pedestrians	0.05-0.2 m	2017
[242]$^{\bullet}_{2}$	Accelerometers	• Tracking: Track Tree Structure • Tracking: Track tree pruning	Multiple pedestrians	0.23-0.36 m	2018
[243]$^{\bullet}_{2}$	SM-24 Geophones 25 kHz	• Localization: TDoA & multilateration • Tracking: Signal decomposition / Wavelet filter	Footstep Surface tap	0.07-0.13 m 0.03-0.18 m	2018
[244]$^{\bullet}_{2}$	SM-24 Geophones 3 kHz	• Tracking: Error-Domain Model Falsification • Tracking: Sequential analysis	Trajectory	$< 5\%$	2019
[245]$^{\bullet}_{2}$	Triboelectric vibration sensor / 3 kHz	• Localization: TDoA and hyperbolic intersections	Tap	$< 10\%$	2019

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

on estimating the location of the footsteps and distinguishing them from different pedestrians. The authors then introduced three tractable algorithms that operate online, updating occupancy count over time as new footsteps are detected. The first algorithm, called *FindTrellisStart*, implements a search procedure for both the first track generation and the subsequent tracks. The second algorithm, called *TrellisForward*, implements stage-wise trellis computations to find footsteps in a viable time window. The last algorithm, called *TrellisTraceBack*, is executed once the forward phase is complete and identifies the optimal path as the one with the lowest total cost. The author (Poston [242]) later presented an approach for tracking multiple building occupants. The constraints are the assumption that the occupants are moving on linear trajectories and that closely-spaced footsteps do not overlap in time. In this study, the author presented a tracking algorithm that receives a sequence of footstep event reports that includes detection time and observed position. The algorithm builds a tree structure where the first footstep is the root node. Several criteria were developed to identify which of the new footsteps might correspond to the first level branches. A track tree pruning methodology is also proposed. The results of this work show a tracking error under 0.36 meters.

For more general applications, Pan et al. [243] presented, in 2018, a structural vibration sensing system that enables various types of human induced excitation (impulse and slip-pulse) tracking under multiple structural conditions. The proposed approach investigates the wave properties of different types of excitations to understand the dispersion, propagation and attenuation of impulse and slip-pulse signals, which are used to design the algorithm that can obtain accurate TDoA estimations. Similar to the work in [240], multilateration is adopted to calculate locations of the excitation sources and hence achieve tracking in [243]. A series of experiments are conducted to evaluate the system by computing the accuracy of locating various types of excitation sources with different structural characteristics. The results show that the proposed platform achieves up to a six times improvement in impulse localization accuracy and a three times improvement in slip-pulse trajectory length estimation compared to the benchmarks in multiple applications.

In most recent works, an alternative model for tracking pedestrians inside a building was proposed by Drira et al. [244] in 2019. The approach aimed to incorporate information from physical-based models to overcome limitations of previous methodologies. Besides segmenting the footsteps using wavelet decomposition and identifying the footstep localization using a threshold that combines uncertainty and target reliability of identification, the work proposed an occupant localization error-domain model-falsification (EDMF) and sequential analysis to estimate the occupant trajectory. The EDMF involves the generation of multiple model instances that are falsified when the prediction instances contradict measurement data. In this case, a candidate location set is extracted from the real footstep location and the combined uncertainty. The sequential analysis is then done to identify the falsified locations resulting from the EDMF. The sequential analysis reduces the population of the resulting candidate locations. In terms of surface tracking, in 2019, He et al. [245] presented a vibration based Human-Machine-Interaction (HMI) with an unlimited sensing area on ubiquitous surfaces. The main idea is that by attaching triboelectric vibration sensors (TVS) on surfaces like doors, walls, and tables, the vibration sources can be located using the TDoA and the ordinary surface can be converted into multi-functional interactive interfaces. A case of study of a authentication system based on TVS-based virtual numeric keyboard was presented. The signal generated by a finger tapping the plate with six keystrokes is captured by the sensors; a localization algorithm based on TDoA is used to locate the position of the vibration source. The combination of multiple locations could track the sequence of taps for authentications purposes.

Table 9 presents a summary of the recent works on pedestrian and surface tracking estimation using vibration sensors. In this type of application, we have identified a potential research area. Note that all the current approaches rely exclusively on SP techniques. So far, we could not identify any approach that utilizes ML for pedestrian tracking.

4.2. Single sensors vs sensor networks

All the discussed approaches for occupancy information inference utilize multiple sensors to achieve occupancy estimation, localization, and tracking. The rationality is pretty simple; more than one sensor is needed to triangulate information to achieve localization, which is indeed an indispensable feature for occupancy and tracking tasks. In fact, large scale deployment of sensors provides valuable data to improve the accuracy of localization and tracking [215]. However, taking advantage of the large scale sensor networks to characterize occupancy, localization and tracking is still an open area in vibration sensors research. The vast majority of these activity characterization approaches combine data from

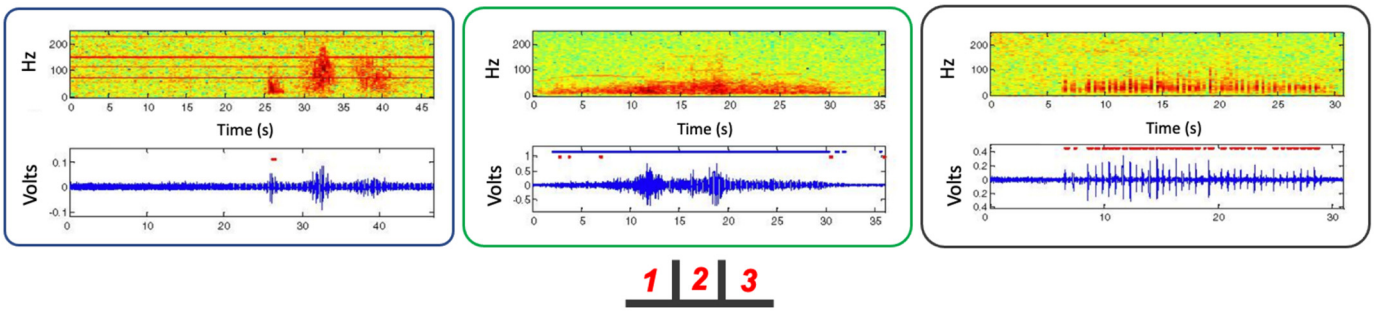

Fig. 9. Examples of time and frequency vibration data from (1) Dog's footstep; (2) vehicle; (3) Person's footsteps. Images from [246].

multiple sensors in an off-line fashion; that means that the current capacity of the sensors to communicate information and "talk to each other" remains unused. Efforts have been done; for example, Pan et al. [205] proposed the use of geophone and Arduino to collectively gather data for occupancy counting using WiFi. In this study, the authors deal with transferring of data and clock synchronization between sensors; however, even though each single sensor data is used to collaboratively determine the walking direction and the number of pedestrians, the approach is not done in real-time, which means that the post-processing of the signals is done off-line. We strongly believe that utilizing real-time in-situ computing could be an excellent direction in the future of indoor characterization with vibration sensors. Furthermore, finding innovative ways to automatically deploy and configure multiple sensors without requiring manual intervention is another interesting path for indoor characterization that has begun to be explored by He et al. [247].

5. Personal safety evaluation

Human identification is one of the main challenges for health and personal safety applications. Specifically, in the personal safety spectrum, the applications to identify authorized users and intruders and applications to detect when a person's fall have taken on new relevance these days. In this section, we explore personal safety in two directions, person identification and fall down detection. We describe the major accomplishments of these applications while using only vibration sensors.

The majority of existing approaches for person identification and fall down employ either wearable devices [248–250], video cameras [251–253], or bio-metrics [254–256]. However, efforts have been done to utilize other non-conventional and non-intrusive sensors for both identification and fall alert; for example using WiFi signals [257–261], passive infrared sensors [262,263], inertial sensors [264], force sensors [265], radio frequency [266], etc. The vibrations sensors have also demonstrated that are capable to generate signals to differentiate persons from other objects and live creatures. For example, Fig. 9 is extracted from the work presented by Park et al. [246] which shows the different types of vibration generated by animals, vehicles and people. Furthermore, other works have used vibration sensor to identify exactly the person as the footsteps patterns are considered unique from person to person [267,268]. Those works illustrate the potential of non-intrusive vibration sensors to identify people and most importantly, identify fall downs.

In this section, we explore the different signal processing and machine learning techniques that have been used in personal safety (Section 5.1). We also present the different types of sensors and/or sensor networks used for each approach (Section 5.2).

5.1. Data analysis techniques

Similar to occupancy information inference, the data analysis techniques for personal safety evaluation vary depending on the type of application. Here, we explore relevant works on person identification (Section 5.1.1) and fall detection (Section 5.1.2).

5.1.1. Person identification

Person identification is a critical step in multiple smart home and security applications. Multiple vibration-based works have been developed to differentiate humans from animals and vehicles, discriminate gender, identify one person among multiple potential people, etc.

One of the first attempts at people identification with accelerometers was made by Ailisto et al. [269] in 2005. The method was a significant shift from the mainstream gait recognition research relying on computer vision [270–272] or other types of sensor installed on the floor [273]. The authors in [269] developed a gait recognition method, which uses the acceleration signals producing by walking. The walking person has to carry a mobile device (in this experiment one laptop) with an accelerometer. Only one sensor was used for this work, and only signal processing techniques were employed. Using the three-channel accelerometer (x, y and z), the method aims to generate a "gait code" composed of the average x (forward), z (vertical), and acceleration signals for a and b steps. a and b are the "right" and "left" steps. The identification phase starts with the generation of current c and d gait codes as in the training phase. Then, a comparison of the current gait with the enrolled gait is performed using cross-correlation. A threshold T is used to evaluate whether the correlation coefficient average is accepted or rejected for identification. The accuracy is reported between 72% and 88%. However, the method is prone to errors due to changes in the speed of walking, change of shoes, and ground. Also, in 2005, Mantyjarvi et al. [274] used a similar methodology. A person carries a portable device. Only one sensor was used for this work, and only signal processing techniques were employed. The data is first normalized to a range of -1 and 1 and then it is processed using correlation. Unlike [269], authors add frequency-domain methods and data distribution statistics. The motivation of using frequency-domain methods is based on the assumption that there is a characteristic distribution of frequency components for each person in the walking signal. The data distribution statistics were added under the assumption that characteristics of the signal shape affect the data distribution. A comparison of the current step models with the templates is performed with cross-correlation similar to [269]. Also, the authors calculated the Fast Fourier Transform (FFT) for the signals x and z of the accelerometer. The first 40 FFT coefficients per channel are concatenated as a feature vector and used for identification. Also, 10-bin histograms normalized by the length of the data are composed of x and z acceleration signals. The histogram is concatenated as a feature vector. Also, third and fourth-order moments

are calculated as a feature vector. All these feature vectors are used in conjunction with the correlation to accept and reject the identification. The accuracy of the method is ranged between 60% and 85%.

Another effort to person identification with vibration sensors was made in 2008, Park et al. [246] presented a technique to discriminate between vehicles and human footsteps using a Dynamic Synapse Neural Network based on vibration sensor data. The approach also had the feature of eliminating quadrupeds' footsteps. Later in 2009, Park et al. [275] utilize a seismic vibration sensor to discriminate human footstep from quadrupeds. They proposed a Cadence-based analysis of temporal gait pattern to see the statistical difference between walking of humans, horses, and dogs. The overall accuracy was 95%. In the same line, Mehmood et al. [276] presented in 2012 a method to discriminate bipeds from quadrupeds. Specifically, the authors collected vibration data from humans and horses using geophones on the floor. The data was processed and features were extracted to apply an SVM classification (binary classification). They achieved an accuracy of more than 90% on signals of length 15-20 sec. Xin et al. [277] also have classified vehicles, humans, and animals with PIR and seismic (vibration) sensors. The authors used Wavelet Transform and Probabilistic Finite State Automata (PFSA) for feature extractions. With the help of seismic sensors, they achieve an accuracy of 97.3% for humans and animals.

In 2015, Pan et al. [267] presented a pioneer work on person identification with non-intrusive vibration sensors. The system detects signals induced by footsteps, extracts features from these signals, and applies a hierarchical classifier to these features to identify each registered user. The signal is gathered by a "sensing hardware", which consists of a geophone, an amplifier, and an analog-to-digital converter (ADC). Multiple sensors are using in this approach and no communication between them is required as the results are made off-line. This sensor used a sampling rate of 25 kHz. The "step extraction" is done by modeling the noise as a Gaussian distribution and then apply an anomaly detection method to extract step events. The threshold value to detect a step event is determined by an allowable false alarm rate. Once the events are extracted, the system performs the "feature extraction" by using only the normalized signal of the first five steps closest to the sensor that has the highest Signal-to-Noise Ratio (SNR). For each step, the system computes time-domain (standard deviation, entropy, peak values, partial signal before and after the maximum peak, etc.) and frequency-domain (spectrum centroid, location, and amplitude of peaks, power spectrum density, etc.) features. Then, the system conducts a "step level classification" by taking features of step events from different people's traces to generate a classification model using Support Vector Machine (SVM), which maximizes the distance between data points and the separating hyper-plane. The multi-class C-Support Vector Classifier (C-SVC) [284,285] from LIBSVM library [286] is applied with the Radial Basis Function (RBF) kernel to perform the non-linear separation. The step level classification with LIBSVM gives out both the identification label and the confidence level as the result of testing the step event. The accuracy of the system was enhanced by using a confidence level threshold that allows to determine whether the classification result of the trace is reliable enough for identification. The system achieves over 83% identification accuracy when identifying every trace for five people. Also, trace level classification improves to 96.5% when the system focuses on the top 50% traces that are more confident.

Later in 2017, FootprintID, an indoor pedestrian identification system that utilized footstep-induced structural vibration was presented by the same group of Pan et al. [278]. The system identifies a pedestrian through his footstep-induced vibration. The walking speed and step location variation of footsteps is characterized and utilized to achieved robust person identification. Multiple sensors were deployed, and machine learning techniques were used for identification. In this paper, the authors present a transductive learning algorithm RTSVM and an improved ITSVM that dynamically updates the model of the labeled data based on the walking speed and step localization of a person's footstep to extend the classifier and to handle extreme cases. The system achieved an accuracy of 96% and 3X faster than normal Support Vector Machine approaches. The same year, Anchal et al. [279] present an approach to predict the gender of a person from their footfalls using a vibration sensor. They tested various machine learning machine techniques on their dataset. Using a Linear-SVM, the authors achieved an accuracy of 94.56%.

Mukhopadhyay et al. [280] presented an approach to detect intruders and predict his/her state of motion using geophones. The authors proposed an event extraction technique for detecting footfall events and extracting portions of the signal that correspond to an event. Then, using a Support Vector Machine with a Gaussian Kernel (SVM-RBF), the authors predict presence. Later, in 2018, Han et al. [281] presented a person identification application using accelerometers and gyroscope. The approach was based on the extraction of multiple features in the time and frequency domain, and on the utilization of a Gaussian Support Vector Machine for training and testing modules. When multiple occupants were in the same place, a multi-class SVM was used to identify each one of them. The application reached around 96% of accuracy on identification without labeled training data. For the unknown labels scenario, the authors utilized a hybrid approach of unsupervised and supervised learning techniques. Similar to the known labels scenario, the history data was used to process and extract features. They used clustered indices as quasi-labels that substitute the ground truth labels. Quasi-labels represent different clusters, or groups, corresponding to the history data. While clustering algorithms such as K-Means provide linear decision boundaries, the authors in this paper designed an approach called *SenseTribute* using classification as the backbone framework for the simplicity of integrating both known and unknown labels scenarios.

In 2019, Clemente et al. [268] present an indoor person identification approach using geophones. Similar to other works, the author used time-frequency feature extraction and a support vector machine for identification. The innovation of this work was the introduction of an in-situ real-time voting system to improve accuracy. Each sensor collaborates by transmitting their individual person recognition and the energy event. The unit with the highest event energy calculates and identifies the person. The approach reached an accuracy of 93.75%. The same year, Anchal et al. [282] proposed a person verification system based on footfall signatures using Gaussian Mixture Model-Universal Background Model (GMM-UBM). In this paper, different scenarios were evaluated to evaluate the robustness of the systems. The authors presented a comparison of the Half Total Error Rate (HTER) of the proposed system with other approaches based on SVM, and Convolution Neural Networks (CNN). It turned out that the proposed system over-performs traditional methods up to 46%.

Recently, in 2021, Anchal et al. [283] proposed an unconstrained biometric authentication system that utilizes footstep information collected by geophones. The main advantage of this work is that it does not require any special orientation or positioning of the subject. Registered and unregistered users were used for multiple tests to identify people and intruders. The authors proposed the use of an unsupervised learning-based event detection/extraction technique called *USLEET*. The proposed method works in training and live phases. In the training phase, an Unsupervised learning algorithm called GMM was used to cluster the samples into two classes, footstep, and noise (absence of an event). In the live phase, signal segmentation, feature extraction, and GMM model are ap-

Table 10
Vibration-based approaches for person identification.

Paper	Sensor	Data analysis technique	Type of recognition	Performance	Year
[274]$^{\bullet}_{1}$	Accelerometer	• Data distribution statistics • FFT and feature vector	Person recognition	Accuracy 60 – 85%	2005
[246]$^{\diamond}_{2}$	Geophone 500 Hz	• Dynamic Synapse Neural Network (DSNN)	Vehicle recognition Human recognition Dog Recognition	Accuracy 93.3% Accuracy 98.3% Accuracy 99.9%	2008
[275]$^{\bullet}_{1}$	Geophone 100 Hz	• Candance-based analysis • Statistical difference approach	Single Human recognition Multiple Human recognition Horse Recognition	Accuracy 98.54% Accuracy 98.02% Accuracy 98.14%	2009
[277]$^{\diamond}_{2}$	Geophone 10 kHz	• Wavelet Transform • Probabilistic Finite State Automata (PFSA) • Support Vector Machine	Animals vs humans discrimination	Accuracy 97.3%	2011
[276]$^{\diamond}_{2}$	Geophone 1 kHz	• Time-frequency feature extraction • Support Vector Machine	Horses vs humans discrimination	Accuracy 90%	2012
[267]$^{\diamond}_{2}$	Geophone 25 kHz	• Time-frequency feature extraction • Support Vector Machine and Trace-Level Classification	Person Identification	Accuracy 96.5%	2015
[278]$^{\diamond}_{2}$	Geophone 1 kHz	• Iterative Transductive Learning Algorithm (ITSVM) • Confidence Threshold	Pedestrian Identification	Accuracy 96%	2017
[279]$^{\diamond}_{2}$	Geophone 192 kHz	• STA/LTA for event detection • Time-Frequency Feature Extraction and Linear SVM	Gender Prediction	Accuracy 94.56%	2017
[280]$^{\diamond}_{2}$	Geophone 8 kHz	• SVM-RBF Classifier • Adaptive Thresholding	Intruder Detection	Accuracy 77-86%	2017
[281]$^{\diamond}_{2}$	Accelerometers 5 kHz Gyroscope	• Time-Frequency Feature Extraction • SVM-RBF Classifier and multi-class SVM	Person identification	Accuracy 96%	2018
[268]$^{\diamond}_{2}$	Geophone 1 kHz	• Time-Frequency Feature Extraction • SVM and in-situ Weight Voting System (WVS)	Person identification	Accuracy 93.75%	2019
[282]$^{\diamond}_{2}$	Geophone 8 kHz	• Time-Frequency Feature Extraction • Gaussian Mixture Model (GMM) • Universal Background Model (UBM)	Person verification	HTER 7%	2019
[283]$^{\diamond}_{2}$	Geophone 8 kHz	• Unsupervised Learning Event Detection/Extraction Technique • Gaussian Mixture Model (GMM)	Person identification Imposter Detection	Accuracy 90-94% Accuracy 76-87%	2021

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

plied to extract the event. The approach reached a good performance in multiple types of floors.

Table 10 presents a summary of the recent works on person identification using vibration sensors. In this particular application, the majority of the studied papers utilize ML techniques (eleven out of thirteen) because these approaches rely on a classification method.

5.1.2. Fall detection

Much work has been done in the area of fall detection. Thus far, there are already several other overview papers on fall detection system implementation; for example [287–294]. A vast majority of fall detection systems using vibration data apply the threshold-based methods to detect the fall. Even though those methods are able to detect when a fall occurs, the rate of false positives is high. Also, a single threshold is not as accurate as wanted due to unique person's characteristics and behavior. Thus, to reduce these false positives, machine learning techniques are applied in fall detection systems. Yet not a single machine learning method is widely recognized as most effective and new approaches are still being introduced. Another problem is lack of real-world data. The majority of the works utilize simulated data, which is not as similar to the real-world data as expected. However, we describe here the most prominent works and their techniques for fall detection with vibration sensors. For works developed before 2012, we refer the reader to the survey paper by Bangala et al. [292] that presents multiple fall detection systems based on accelerometers.

Because the vibration signal of environmental noise and footsteps are much different than the signal generated by a fall down, an important number of works for fall detection is based on threshold methods [295–297]. However, the vast majority utilizes machine learning techniques to classify falls from other everyday events. These works are presented in Table 11. For example, Tong et al. [298] introduced, in 2013, a fall detection and prediction method using based on Hidden Markov Model (HMM). The approach used tri-axial accelerometers, and the acceleration time series extracted from human motion processes were used to describe human motion features and falls. The authors also stated that the outputs of the HMM can be used to evaluate the risk of falls. The work reported accuracy of 100%. Later, in 2015, Summer et al. [299] proposed the use of seismic sensors to discriminate fall downs. The system evaluated the use of K-Nearest Neighbor (KNN) and Support Vector Machines (SVM) to classify the events. The best accuracy was achieved with SVM. Other works also incorporate the valuation of multiple machine learning techniques on acceleration data [300]. In these approaches, the sensors were placed on the human body.

The approaches that are based on geophones [301,220] use sensors placed on the floor. For example, in 2019, Huang et al. [301] utilized multiple geophones on the floor to detect falls. In this study, the authors used an HMM fed by features that were extracted using Discrete Wavelet Transform (DWT). To reduce the false alarm rate, the authors proposed a reconfirmation mechanism called Energy-of-Arrival (EoA), which enables the system to achieve fine-grained indoor positioning without high sampling fre-

Table 11
Vibration-based approaches for fall down detection.

Paper	Sensor	Sensor-location	Data analysis technique	Alarm	Error	Year
[298]$^{\bullet}_{1}$	Tri-axial Accelerometer	Waist	• Hidden Markov Model (HMM)	N/A	0%	2013
[295]$^{\bullet}_{1}$	Shimmer Accelerometer	Waist	• Threshold	N/A	0%	2015
[296]$^{\bullet}_{1}$	ADXL345 Accelerometer 100 Hz	Waist	• Threshold	Y	∼ 3%	2015
[299]$^{\diamond}_{2}$	USB-1208FS sensor	Floor	• Wavelet Coefficient Characterization • Spectral Statistics • K-Nearest Neighbor (KNN) • Support Vector Machine	N	 2.3% 0.76%	2015
[297]$^{\diamond}_{1}$	Accelerometer	Chest, waist, arm, hand	• Feature extraction & Support Vector Machine • Threshold	Y	5-7%	2017
[300]$^{\diamond}_{1}$	Accelerometer	Waist	• Logistic Regression • Decision Tree • K-nearest Neighbor • Support Vector Machine • Naive Bayes	N	∼ 5% ∼ 6% ∼ 10% ∼ 4% ∼ 1%	2017
[303]$^{\diamond}_{1}$	Accelerometer	Waist	• Mean and Range feature extraction • Support Vector Machine	N	< 1%	2019
[301]$^{\diamond}_{2}$	Geophone	Floor	• DWT feature extraction • Hidden Markov Model (HMM) • Energy of Arrival (EoA)	Y	∼ 4%	2019
[220]$^{\diamond}_{2}$	Geophone	Floor	• Time and Frequency domain feature extraction • Support Vector Machine	Y	4.86%	2019
[302]$^{\diamond}_{2}$	Accelerometer	Floor	• K-Means clustering and K-Nearest Neighbor algorithm	Y	∼ 5%	2021

(•) Signal processing data analysis. / (◇) Machine learning data analysis.
(1) Only one sensor is used. / (2) More than one sensor is used.

quency. The accuracy of this work was about 96%. In the same year, Clemente et al. [220] also proposed a fall detection mechanism based on deployed geophones. In this case, time and frequency domain features were extracted to feed a Support Vector Machine that classifies the fall from other events. The innovation of this work is that besides detecting the fall, the localization of the fall is also estimated.

In 2021, Shao et al. [302] developed a framework of using floor vibration to build the pattern recognition system in detecting human falls based on a machine learning approach. They conducted fall experiments with a scaled 3D-printed human body model's fall. The human body model with twelve fully adjustable joints they built is 1:4 to actual human body size with consideration of body part lengths, connecting main joints, and body weight proportions. The model is used to simulate a conscious person who is capable of controlling all of his limbs and standing up straight or an unconscious person unable to control his body by tightening or loosening the screws on the model. The vibration from model's falls is recorded with a mobile phone with a built-in low-sensitivity accelerometer, intended to detect human falls. The sample frequency of the test is 100 Hz. The acceleration data collected show that there is rapid attenuation after the fall. They also experimented object drops using a ruler with the same weight as the body model. The object is dropped from the same height as the center of gravity of the model. The vibration data is recorded from the time of the fall to the end of the last rebound. The experiments with human body model fall and an object fall intended to observe whether the floor vibration frequencies can be differentiated. They conducted a total of 314 experiments (107 object drops, 97 body model forward falls, and 110 body model backward falls).The detection accuracy was over 90%.

With the increasing aging of the population and the potential risk of falls, it is certain that more approaches using non-intrusive methods such as vibration sensors will come out as an alternative to traditional person-intervention approaches. Table 11 presents a summary of the recent works on fall detection using vibration sensors. Note that the majority of the studied papers (six out of nine) rely on ML techniques because the classification of the falls is a critical task on these types of approaches.

5.2. Single sensors vs sensor networks

Similar to indoor characterization approaches, the methodologies proposed for personal safety (person identification and fall detection) are based on the use of multiple sensors. Then, the opportunity to take advantage of sensor networks is prominent. In fact, works like the one presented in [268,220] utilize sensor communication and in-situ computing to identify people and to locate falls. These works open the door to multiple applications in which sensors can compute in real-time and collaborate with each other. These kind collaborative approaches will be likely to lead the efforts for smart home applications in the new era.

6. Infrastructure health monitoring

The original motivation of the infrastructure monitoring is to detect the seismic damages to buildings caused by the shaking and damage from earthquakes [308]. Later, monitoring works are developed to handle the continuously changing environments subjected to not only earthquakes but also other natural hazards such as storms and hurricanes, and artificial/anthropogenic hazards such as explosions [309]. Vibration sensors have been used to detect and monitor the infrastructure health. The concept of infrastructure can be broad, including multi-story building [308], super high-rise building monitoring [304], radioactive waste repository [310], dam health monitoring [305], train-triggered building monitoring [306], tunnel monitoring [307], mine planning [311,312], etc. Vibration signals can be viewed as an important resource for monitoring infrastructural health, or locating damages.

Fig. 10 shows some representative vibration-based infrastructure health monitoring applications. In general, the infrastructure

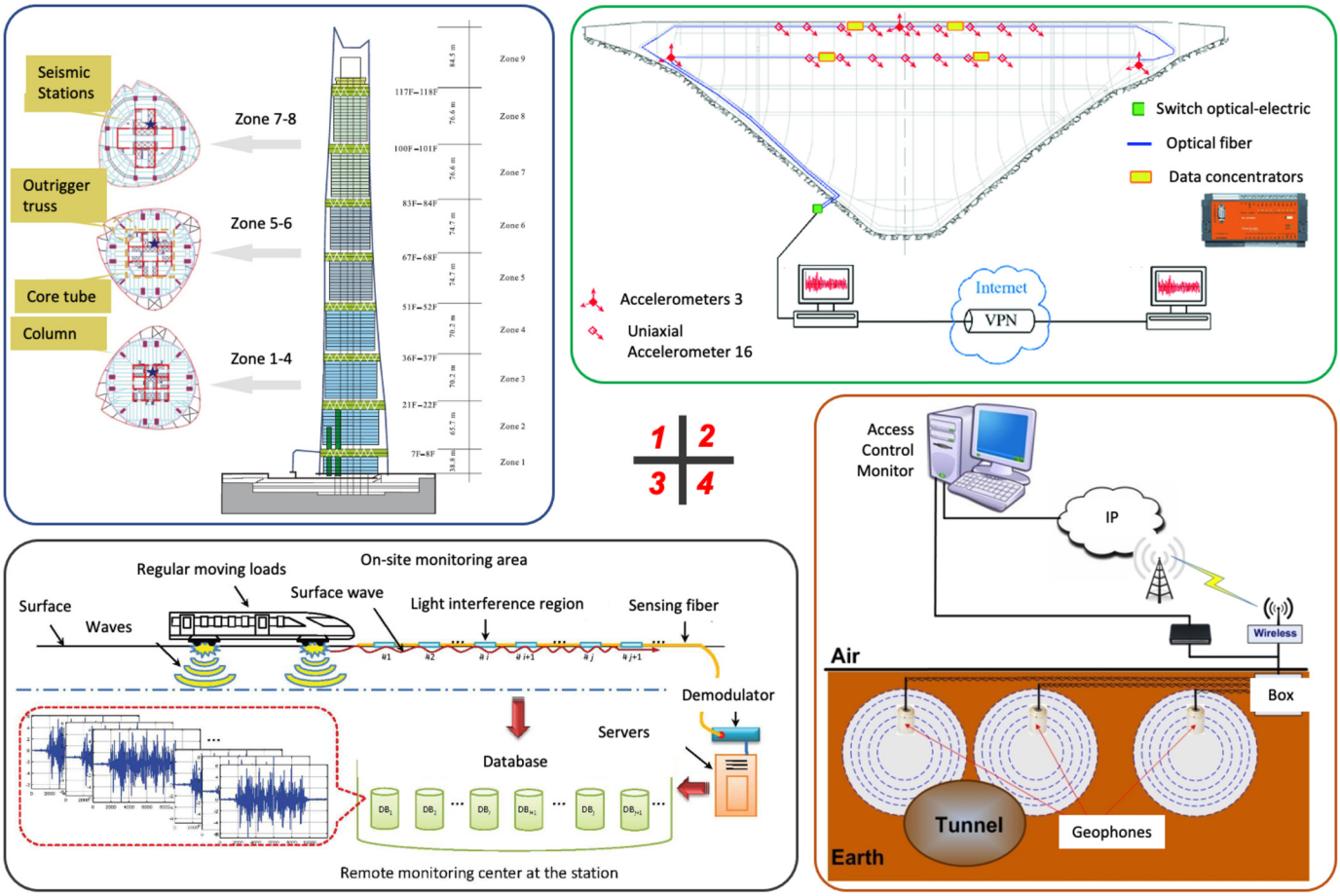

Fig. 10. Infrastructure health monitoring based on vibration sensor networks. (1) super high-rise building monitoring [304]; (2) dam health monitoring [305]; (3) train tracking [306]; (4) tunnel monitoring [307].

health cannot be effectively monitored using single vibration sensor which cannot characterize the properties of the whole infrastructure. Instead, sensor networks are typically adopted, for example, a broadband seismic land streamer for urban underground infrastructure was proposed by Malehmir et al. [313] and sensors deployed on multiple stories of a building was adopted by Wu et al. [304]. The recent developments of instruments and methodologies make it possible to apply seismic imaging techniques to building health monitoring using spatially dense seismometer arrays, as shown in Lin at al. [314].

The Community Seismic Network (CSN) is one good example of the low-cost networks [316,317]. Now it is possible to analyze continuous vibration data on a small spatial scale and with a high spatial resolution, thanks to the deployment of multiple triaxial accelerometers per floor of the building. Seismometers, such as geophones, are typically employed for the infrastructure health monitoring. Also, other accelerometer sensors are deployed, for example, the low-cost microelectromechanical systems (MEMS) technology sensors become more and more common in the high-rise building monitoring with a 200 Hz or higher sampling frequency. Because the sensor cost is not high, it is possible to install vibration sensors at high densities over small areas, such as the urban region of the Los Angeles basin as proposed by Clayton et al. [317]. In addition, multiple kinds of vibration sensors can be jointly used, for example, surface sensors and borehole sensors corresponding to different vibration wave types and components are both used for mine planning [311,312].

In this section, we explore the different signal processing techniques that have been used for infrastructure monitoring (Section 6.1). We also discuss the use of sensor networks in these kind of applications (Section 6.2).

6.1. Data analysis techniques

In terms of vibration data analysis techniques, different data processing and feature extraction methods have been proposed and developed for different applications. In this survey, we roughly divide them into two categories: structure property imaging (discussed in Section 6.1.1) and waveform feature extraction (discussed in Section 6.1.2). Fig. 11 demonstrates four examples where two are related to structure property imaging and the other two are related to waveform feature extraction. For example, Fig. 11-(1) show the method of anisotropic traveltime inversion where objects can be located underground [310], Fig. 11-(2) shows the 3D tomography velocity estimation visualization results [313] from an array of geophones in a big field. Fig. 11-(3) illustrates a comparison of the impulse response functions (IRFs) and horizontal to-vertical spectral ratio (HVSR) for all floors of a building [304], and Fig. 11-(4) illustrates different seismograms of a building, relative travel time, envelope amplitude, spatial gradient, and the seismic velocity obtained by vibration sensors [315].

Ambient vibration noise has been used for the building dynamic property characterization [318–320,319,321,315]. Inspired by seismic ambient-noise interferometry techniques, Snider et al. [322] first applied the seismic interferometry technique to the ambient earthquake data acquired by a sensor networks to monitor the Millikan Library in Pasadena, California. Seismic imaging techniques can be applied to spatially dense arrays which mea-

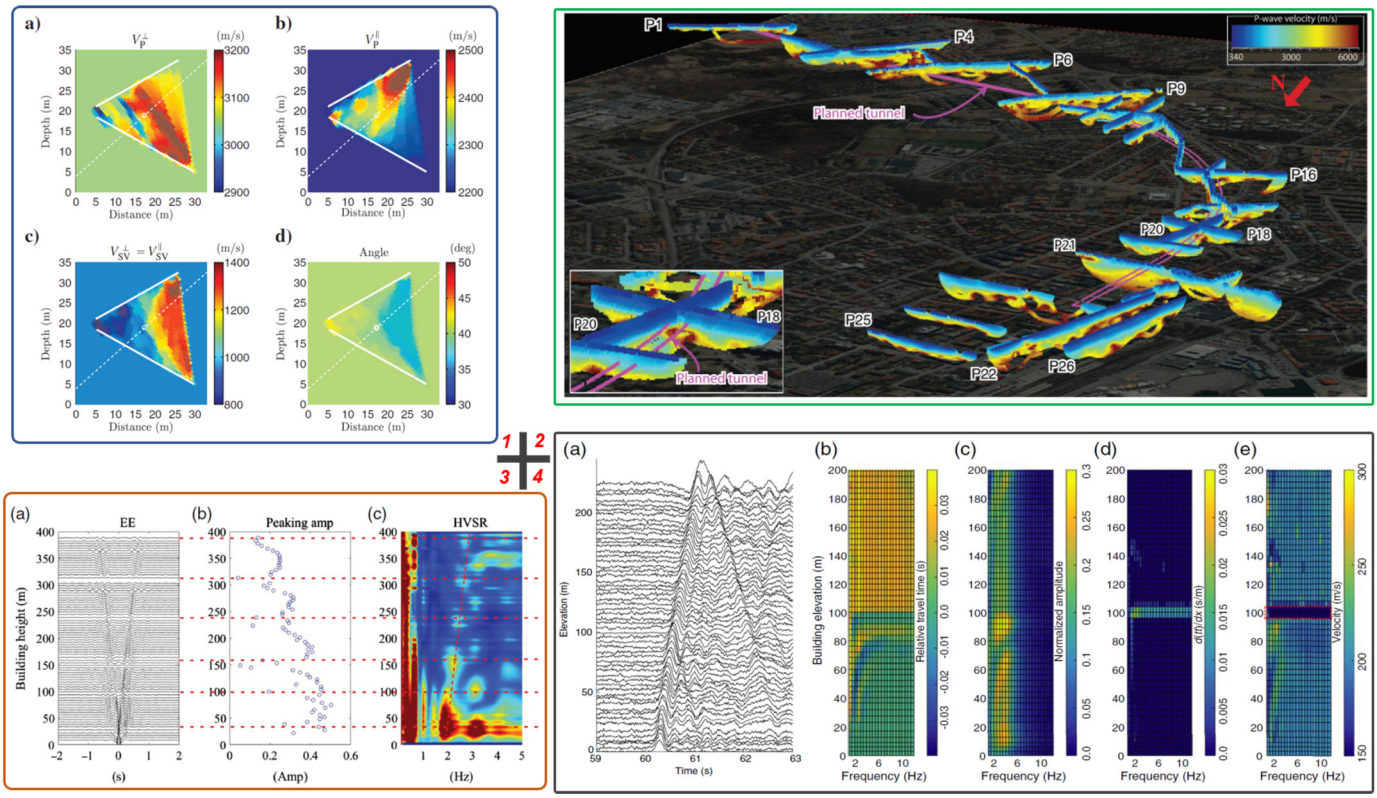

Fig. 11. Examples of different infrastructure health monitoring methods. (1) Results of anisotropic traveltime inversion, a.k.a. structure velocity [310]. (2) The 3D tomography velocity estimation visualization results [313]. (3) Comparison of the impulse response functions (IRFs) and horizontal to-vertical spectral ratio (HVSR) for all floors [304]. (4) Seismograms, relative travel time, envelope amplitude, spatial gradient, and the seismic velocity [315]. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

sure vibration signatures between pairs of vibration sensors via cross correlation as proposed by Valero et al. [323]. The ambient building responses to vibrations are recorded by accelerometers, then the signals from a dense seismic array of three-component nodal seismometers are adopted in the seismic ambient noise interferometry, which can provide the infrastructure dynamic information [318].

The data processing procedure for extracting propagating vibration signals from ambient noise has been largely stabilized and shown sufficiently good performances [324]. In general, the procedure includes three phases: (1) single-station data preparation, (2) cross-correlation and stacking to a desired time-series length, and (3) dispersion measurement as well as velocity estimation. Note that this procedure can be entirely autonomous to effectively and efficiently process large sensor data streams from sensor networks deployed on large-scale infrastructures [325].

6.1.1. Structure property imaging

In single-station data preparation, denoising and normalization have been applied to remove the interference and contamination from earthquakes, instrument irregularities, and other noise sources near sensors, such as human activities and weather events. In addition, besides all kinds of filters such as bandpass filter, spectral whitening and similar operations can also be used to enhance the signal bands of interest. Next, cross-correlations will be computed and stacked to extract the Green function, based on which group and phase velocities can be measured using frequency–time analysis (FTAN) on the dispersion curve [326,323,191]. For structure imaging, the majority of the works used signal processing techniques with certain modifications of similar methodology, like the one presented in Fig. 12.

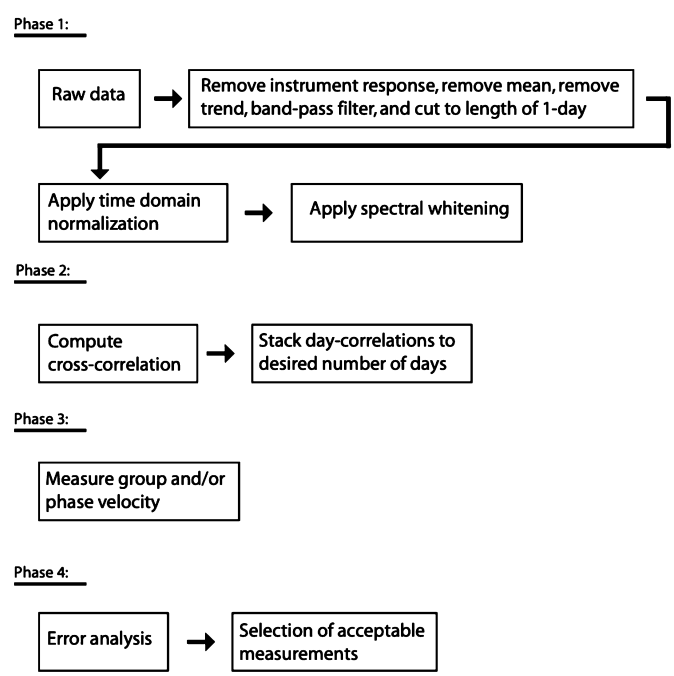

Fig. 12. Schematic representation of the data processing scheme for structure property imaging. Image from [324].

Specifically, the building vibration responses can be estimated using impulse response functions (IRFs), which can obtained following [322,318]:

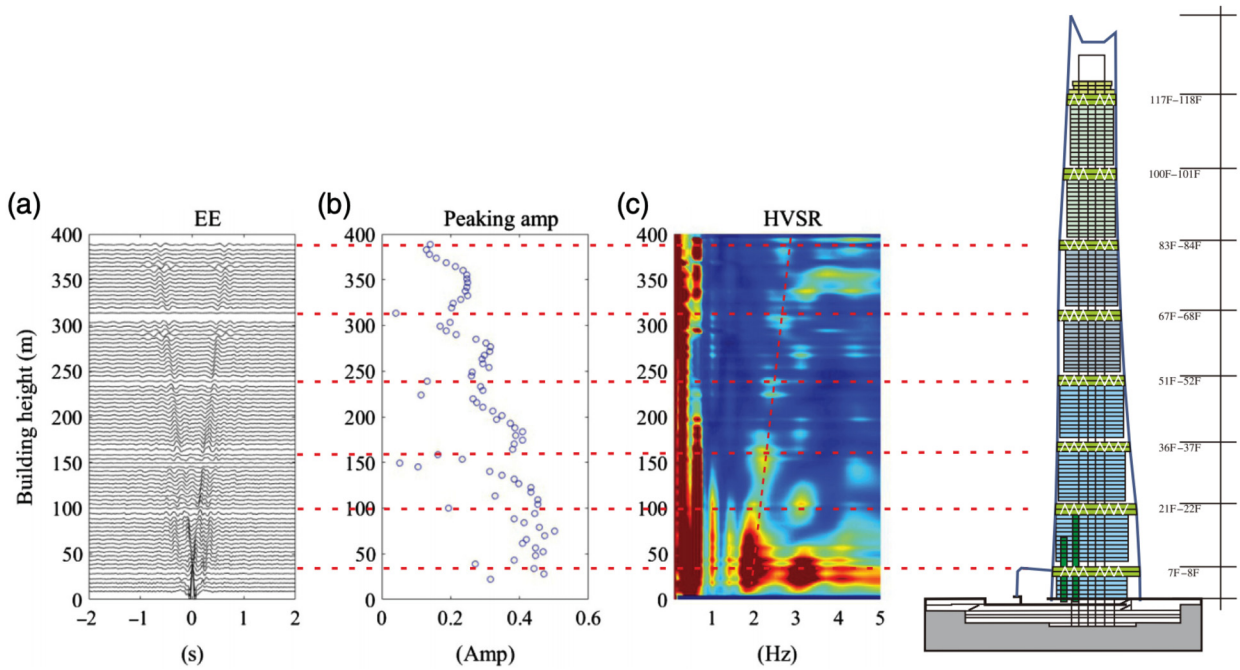

Fig. 13. Three different waveform features to analyze building health, specifically refuge floors extracted from [304]. (a) EE crosscorrelation component of the signal, (b) Peaking amplitude, and (c) Horizontal to-vertical Spectral Ratio (HVSR). In this study, first floors are refuge floors. The different features provides an idea of the quality factor of those floors.

$$D_{ij}(z_n, z_2, t) = \left\langle \mathfrak{F}^{-1}\left(\frac{v_i(z_n)v_j^*(z_2)}{|v_j(z_2)|^2 + \varepsilon}\right)\right\rangle, \tag{1}$$

where, the asterisk '*' denotes complex conjugate; i and j represent the ith component of the receiver station and the jth component of the virtual source station, respectively. $\mathfrak{F}^{-1}$ indicates the inverse Fourier transform, and the brackets denote stacking in the time domain [327]. In addition, ε is the stabilization factor, which can be defined as 1% or 2% of the average spectral power, to make the deconvolution calculation numerically stable. Note that the IRFs of different signal components can be obtained using vibration sensors deployed in the different locations in the infrastructure. These IRFs are used to create an image of the infrastructure that can help on the monitoring of its general health.

6.1.2. Waveform feature extraction

Another data processing technique that has been widely used for infrastructure monitoring is the analysis of the Waveform. The infrastructures can be approximated as a continuum, so different material properties can be extracted to characterize the variations [315]. Low-cost vibration sensors and sensor networks make it possible to instrument infrastructures on a floor-by-floor scale. In addition, the continuous vibration recordings at high sampling rates provide the opportunity to acquire the dynamic information.

Compared with the structure property imaging which typically characterizes the infrastructure health based on the seismic velocities, waveform feature extraction techniques provide other characteristics, such as Fast Fourier Transform (FFT) frequency responses [328,329], quality factor [318], power spectral density (PSD) [330], horizontal to-vertical spectral ratio (HVSR) average PSD [304], etc., and have been widely adopted in various types of structures to detect damages.

Waveform feature extraction of the propagating vibration waves leverages the success of high-resolution velocity imaging techniques applied to sensor networks deployed in the buildings to detect and map the potential damage signatures in vibration waveforms. For example, a recent work presented by Wu et al. [304], extract features directly from the waveform signatures of a building to evaluate the quality factor (Q) of the refuge areas. A refuge area is a building area designed to hold occupants during a fire or other emergency, when evacuation may not be safe or possible. The authors extracted information of multiple sensors deployed on the building and determine the potential damages of the refuge areas; all based on the waveform features. Fig. 13 shows three different building signatures obtained with signal processing techniques to evaluate the refuge floors health. In summary, using the waveform features or signatures, the infrastructure properties can be monitored and damages can be detected.

6.2. Single sensors vs sensor networks

In infrastructure monitoring applications the common denominator is the use of multiple sensors. In order to obtain either an image of the infrastructure or a general overview of the building's health, the signal processing techniques used in all the studied works require the information of an array of sensors. The first works, typically performed manually extraction of the data inside the sensors for post-processing [331,324]. Other works have presented the possibility to remotely extract the data from the sensors [332,333]. Most recently, some infrastructure and subsurface monitoring techniques have taken advantage of sensors capabilities and have proposed in-situ computing methodologies, in which sensors are able to process the data in the field and collaborate with each other for generating infrastructure images [190,192,323]. For example, Valero et al. [323] presented a comprehensive evaluation of an array of sensors that collaborate with each other to imaging a subsurface pipeline. The evaluation included the bandwidth utilization of the sensors, the communication cost, and the packet lost influence on the results. We believe that this trend is going to continue, and more building monitoring applications with smart vibration sensors will be available in the near future.

In summary, infrastructure health monitoring researches focus on analyzing the infrastructure properties based on vibration sensor networks. Although the data analytics methods could be similar, due to the different environment, variant events, sensor prop-

erties, and so on, researchers need to modify their methodologies according to their applications.

7. Future research trends

The use of non-intrusive sensing for health and safety is achieving promising results. There are many research directions that can be further investigated, and we envision the following seven possible areas.

7.1. Collaborative vibration-sensing approaches

Instead of manually collecting the data from the sensors or perform off-line estimations, we believe that new approaches will consider exploiting the advantages of current sensors and networks. This kind of approach will be the base for future work in which multiple sensors can independently interact with each other to perform estimations. Some studies have been started to introduce this kind of vibration sensors interactions [191,192,205,220,268], and we strongly believe that this will be one of the important paths for vibration data research.

7.2. Physical-aware and self-configuration

Another promising path is the incorporation of physical-informed and self-configuration sensing as it was initiated by He et al. [247]. Incorporating physical phenomenon knowledge to sensing will increase the accuracy of multiple applications such as vital sign monitoring and fall detection. Also, self-configured sensing system will provide a way to minimize human intervention and training data. Deep learning may bring more opportunities for vibration-based systems, which simplifies the deployment and makes the systems configuration-free.

7.3. Learning techniques for health monitoring with vibration

As presented in this paper, few studies have used learning techniques to monitor and assess human health from vibration data. With the exception, for example [36,71], the majority of the approaches to estimate heart and respiration rates are based on pure signal processing techniques. While these techniques are fast and computer-economic, the use of more advanced machine learning techniques based on the signal processing features may provide useful information to infer the health status of the subject. The same can be applied to infrastructure monitoring, where the approaches are based on signal analysis only. We envision that machine learning will be applied as a routine in future health monitoring based on vibration.

7.4. Multi-people sensing

Sensing, monitoring, and tracking multiple people at the same time is still an open problem in vibration-sensing approaches. Some works have claimed the tracking or monitoring of more than one person [52,70]. However, those approaches can only separate two people's walking or hearts. The use of high-resolution vibration sensors can help to generate fine-grained signals and the application of more advanced techniques for source separation. We envision that multi-people approaches will be ruling the research on vibration-based applications as more practical scenarios need to be tested for the final incorporation of these technologies in the real world.

7.5. Analysis of the dynamic nature of vibration

Due to the complicated and dynamic nature of vibration in the real world, the majority of the applications are data-driven. Nowadays, multiple efforts have been done to test the approaches in diverse scenarios to guarantee results stability. For example, Clemente et al. [35] tested their vibration-based sleep monitoring system on multiple houses, mattresses, and floor structures. Mirshekari et al. [219] and Clemente et al. [220] detected footsteps in different floor structures. However, analyzing and understanding the nature of vibration in different structures is still an open problem that requires more studies to develop techniques that overcome the heterogeneity of the vibration signal.

7.6. Privacy of the data

In the papers that have been studied in this survey, there is no further consideration of data privacy. In certain types of applications, like human health monitoring, personal behavior and person identification, the privacy of the studied subjects is a fundamental piece of those monitoring systems. Even though the data that comes from vibration sensors can be easily de-identified [334], there is a demand for researchers to develop privacy-preserving solutions such that: 1) data privacy is protected during transmission to the Cloud or other devices, 2) sensory data will not be abused by adversaries to infer user sensitive information. This is, without question, a research opportunity for the community.

7.7. Extraterrestrial bodies analysis

Vibration sensors have been used by the National Aeronautics and Space Administration (NASA) in the InSight mission [335] that deployed a single seismic station on the Martian surface in 2018. We envision multiple signal processing and machine learning approaches, used with vibration sensor data, can be used for extraterritorial explorations. In the past, the correlation of seismic noise has been utilized to measure the subsurface velocities in extraterritorial bodies like moon [336]. We believe that multiple collaborative vibration sensors can be deployed in environment-resistant sensors that can use a sensor network to study underground properties in other planets.

8. Conclusion

In this paper, we surveyed state-of-the-art vibration-based systems and applications for health and safety. We discussed the signal processing and machine learning techniques used in these works. Overall, vibration-based sensing is a promising technology from a broad spectrum of smart home and environmental applications. These however have yet to be a replacement for conventional sensing mechanisms due to the initial configuration requirements and lack of integration with real-time collaborative sensor networks. The recent advances in machine learning and deep learning may offer great help for developing configuration-free systems. In terms of human health assessment and monitoring, we showed that vibration sensors have been widely used for heart and respiration rate estimation and sleep monitoring. However, the majority of the used techniques rely on signal processing approaches, which leaves space for more research based on machine learning techniques. In terms of safety applications such as personal identification and fall detection, the vast majority of prior works rely on the use of machine learning techniques; however, the main problem is still the differentiation of multiple sources from multiple people generating vibration at the same time. This survey shows the potential of vibration-based technologies for a wide variety of applications. We believe that there are still multiple properties that can be studied and used to continuously leverage this non-intrusive technology. As presented in Future Research Trends (Section 7), there are still multiple areas and challenges that need to be addressed in the coming years in order to standardize the

use of vibration-technologies in today's human and infrastructure safety/health monitoring.

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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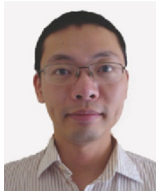

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