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SURVEY PAPER

Vibration-based pervasive computing and intelligent sensing

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Abstract
We are now in the era of the Internet of Things (IoT). Various smart devices can upload their sensor data that characterize our physical world's environment to the server. The researchers benefit from sufficient data to conduct a series of intelligent sensing research, which enhances our daily experience. However, few of the device-free sensing applications using wireless signals have widely penetrated the real-world. In recent years, the underlying property of mechanical vibration is exploited in many sensing applications. Vibration offers a brand new perspective on how we think about intelligent sensing. Leveraging the vibration signal for sensing is possible to break the bottlenecks encountered by other sensing technologies. In this paper, we first provide a technology overview of vibration models and property that has been widely used in recent years. We then survey the existing vibration-based intelligent sensing systems and summarize the representative work in terms of localization, user authentication, health monitoring, and communication. The survey concludes with the key challenges and future research direction of using vibration signals for novel human-centric sensing.

Keywords Pervasive computing · Vibration sensing · Vibration communication · Indoor localization · Human activity monitoring · Authentication

1 Introduction

On the basis of the IoT era, with the combination of artificial intelligence technology, all the connected devices will further have the ability of intelligent sensing in the foreseeable future. They will turn into intelligent devices with independent thinking, vision, hearing, touch, and smell. Intelligent sensing technology will surely have huge application prospects and needs in all aspects of consumer and industrial fields, and related research has gradually become hot topics learned over the past decade.

Intelligent sensing technology aims to use sensors in embedded devices (e.g., vision sensors, acoustic sensors, optical sensors, wireless radio frequency transceiver, inertial measurement units, etc.) to digitally characterize everything happens around the device in the physical environment. As for data analysis, the dominant approach is to put the data sets obtained using signal processing technology into a series of different artificial intelligence frameworks, and then we can obtain the desired information.

Based on the sensor deployment setting, intelligent sensing can be divided into two categories, namely, device-based and device-free. Device-based sensing requires users to wear one or more wearable devices for individual-level data collection and analysis. Device-free does not require the human body to wear any equipment, but through the infrastructure deployed in the surrounding environment (e.g., cameras, Wi-Fi access points, Bluetooth beacons, ultrasonic beacons, LED arrays, etc.) to collect data for inference. It is more user-friendly and natural not to wear devices. However, it is easier to be affected by variant space, time, and light conditions, and thus it is more challenging and meaningful for the research. Therefore, a large number of scholars are attracted to conduct research on intelligent sensing in the past decade.

Among the current sensing technologies, computer vision is the most mature means. By capturing a large amount of image data, there are already many related works that can provide high accuracy and reliability to some specific sensing applications. However, there are still many limitations for computer vision, such as (1) non-line-of-sight; (2) limited field of view and high deployment density; (3) privacy issues; (4) high power consumption and computation overhead.

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In order to avoid the problems in using computer vision methods while retaining or even enhancing the sensing capabilities of the system at the same time, a large number of researches propose device-free sensing applications based on wireless signals, including RFID (Wang et al. 2019), WiFi (Liu et al. 2019), UWB, acoustics (Chandrakala and Jayalakshmi 2019) and visible light (Pathak et al. 2015). For RFID, the sensing range of low-frequency tags is small, and the anti-interference ability is poor. The sensing range of high-frequency tags such as 2.4 GHz RFID can reach 200 m, but RFID readers and tags' costs are too high. When using WiFi signals, the system may occupy the network transmission bandwidth or need to arrange antennas array to eliminate the multipath effect interference. UWB technology requires sophisticated and expensive hardware to functionalize the ultra-wide bandwidth and accurate time synchronization. Acoustics based system is generally susceptible to environmental noise. For high-resolution ultrasonic, its effective signal attenuation is faster when transmitted in the air, and its penetration and propagation range is limited. What is more, it requires the deployment of ultrasonic beacons, which increase the user overhead. As for visible light, the weak resistance to environmental light variation results in degradation to the system performance. In the case of non-line-of-sight conditions (e.g., dark environment and blockage of walls or objects), the system is even unable to work. In general, it is unfortunate to see that few of the sensing technology mentioned above has widely penetrated the real-world.

However, in recent years, vibration-based intelligent sensing has attracted a large number of researchers. It gives a brand new perspective and provides a possibility to break the bottleneck encountered by today's sensing technologies. This possibility mainly benefits from some advantages of vibration signals, such as (1) compared with the radio frequency signal, the multipath effect of the vibration signal is obviously weaker, and the complex environment above the floor will not severely interfere with the signal propagation; (2) the vibration signal can penetrate through the wall, and the propagation range and unit effective range is larger; (3) the cost of the vibration sensor is low, which contributes to large-scale deployment; (4) the system hardware is relatively simple but supports a variety of different applications.

In this paper, we investigate the state-of-the-art vibration-based sensing studies on human-centric applications. Based on the application scenarios, we broadly divide these studies into four categories: localization, user identification, health monitoring, and communication. Specifically, localization involves indoor scenarios (e.g., locating an occupant in a room) and the localization of finger interaction on the physical plane (e.g., table surface) and body skin. User identification mainly focuses on extracting vibro-biometrics from on-body vibration signals and identify users in a non-traditional way. Health monitoring ranges from monitoring daily indoor activity (e.g., walking gait and fall) to analyzing self-induced body vibration (e.g., the vibration of joint motion, muscular movement, and heartbeat). Communications refer to transmit effective signals through vibration wave and the eavesdropping of secret information through vibration channel. The contributions of this paper can be summarized as three-fold:

- We provide an overview of some key models and techniques presented in the recent literature and discuss them in a more detailed way. We believe this will inspire researchers to explore the vibration property further and propose more novel applications.
- We present the first comprehensive review of literature in the field of vibration-based intelligent sensing. We broadly categorize the literature into localization, user identification, health monitoring, and communication, enabling researchers to get up to this emerging field quickly.
- We also present the discussion of limitations and future treads regarding vibration-based intelligent sensing.

The remainder of this paper is organized as follows. We first review some key vibration models and properties used in recent literature to perform vibration sensing in Sects. 2 and 3. Then in Sect. 4, we introduce the four categories of vibration-based intelligent sensing applications. In Sect. 5, we discuss the limitations and the prospects of vibration-based sensing. Finally, we conclude the survey in Sect. 6.

2 Vibration model

2.1 Single-of-freedom model

The vibration-based sensing applications we discussed mainly focus on the mechanical vibration caused by an external force. The externally applied force imposes its energy into the mechanical system and causes displacement of the system. If the applied force is harmonic or can be modulated by a vibration generator, we term it active vibration. In opposite, a random or a natural applied force, like a finger tap or heartbeat, whose vibration pattern is unpredictable and unmodulated, is taken as passive vibration. To model the response of a system to external excitation, we typically consider the spring-mass-damper (SMD) model with a single-degree-of-freedom (SDoF) as starting (Rao 2010). The SMD model can reveal the motion characteristic in a simplification way by considering the mass m, spring coefficient k, and damping c of the system, as shown in Fig. 1.

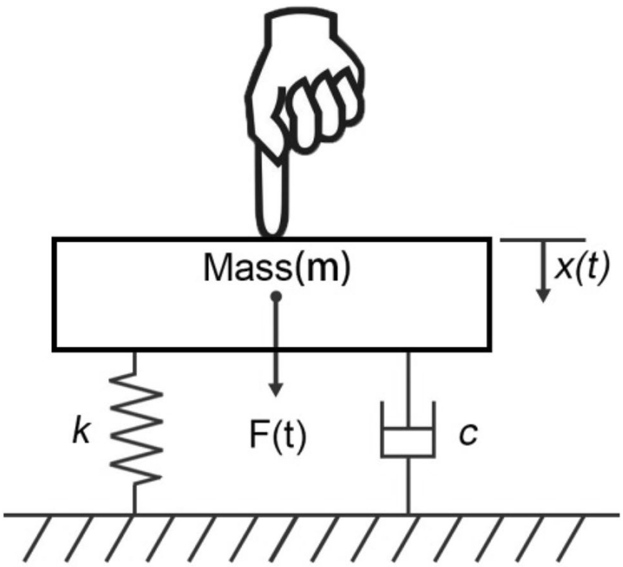

Fig. 1 Illustration of single-degree-of-freedom model (Chen et al. 2019)

When a harmonic excitation $F(t) = F_0 \cos \omega t$ is applied to the rigid body, we have the following differential equation of motion based on Newton's Second Law:

$$F_0 \cos \omega t = m\frac{d^2x(t)}{dt^2} + c\frac{dx(t)}{dt} + kx(t). \tag{1}$$

We can assume the particular solution of Eq. (1) to be:

$$x(t) = X \cos(\omega t - \phi), \tag{2}$$

where X and ϕ indicate the amplitude and phase of the responding vibration wave. By substituting Eq. (2) into Eq. (1) and using trigonometric relations, we have the solution of Eq. (1) as:

$$x(t) = \frac{F_0}{\sqrt{(k - m\omega^2)^2 + c^2\omega^2}} \cos(\omega t - \phi), \tag{3}$$

$$\phi = \arctan \frac{c\omega}{k - m\omega^2}. \tag{4}$$

The solution describes the particle movement of the vibration source. Based on the SDoF model, a more complex and accurate model with multiple degrees of freedom can be deduced and analyzed.

2.2 Three states of vibration

If there is a pendulum dropped from its equilibrium position and left to itself, it will oscillate with natural frequency ω_0. When a harmonic excitation with frequency ω is applied to the mechanical system with natural frequency ω_0, the actual motion of the system is a kind of superposition of vibrations at two frequencies ω and ω_0. At the beginning of the excitation, where two kinds of vibrations frequency are both prominent, is termed as *transient-state*. After a certain time, the system is mainly dominated by the undiminished excitation at frequency ω, and the system moves on to steady-state (French 1971). When the external excitation is dismissed, the system turns into decaying-state and dies away eventually for the mechanical energy is depleted by the damping over time. The differential equation of motion in decaying-state is given by

$$m\frac{d^2x(t)}{dt^2} + c\frac{dx(t)}{dt} + kx(t) = 0. \tag{5}$$

Without an external force, the amplitude of wave attenuates over time. By calculating the ratio of amplitude between two successive periods, we have the decaying factor Λ as:

$$\Lambda = \frac{X(t)}{X(t+T)} = e^{T\frac{\beta}{2m}}. \tag{6}$$

Figure 2 gives an illustration to the three states of the vibration signal that is generated by a smartphone's motor. The vibration frequency of the motor is stable. The motor is activated for 90 ms and then paused for 10 ms (marked as C). In transient-state (marked as A), the vibration frequency change over time and the frequency variance is much larger than the steady-state (marked as B).

3 Vibration wave property

We discuss the vibration of a system which is regarded as an equilibrium point using the SMD model in last section. Then we will present the property of vibration wave that propagates from a vibration source. We mainly present the properties that are leveraged for intelligent sensing field.

3.1 Vibration wave propagation

Before we address the vibration-related problem, we first have to investigate the propagation and attenuation characteristics. It is intuitive that the vibration wave will lose energy during the propagation from one position to another due to the propagation medium's damping. The relationship between the attenuation of amplitude and propagation distance can be modeled as (Abdullah and Sichani 2009):

$$A(d) = A_0 e^{-\alpha d}, \tag{7}$$

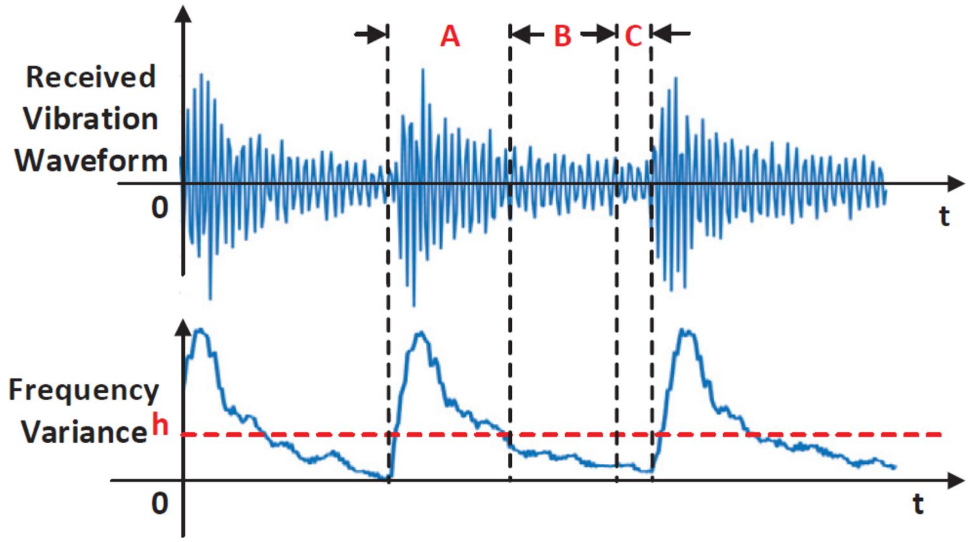

Fig. 2 Frequency variances of three states in vibration (Xu et al. 2020)

where A_0 is the initial amplitude of vibration source, d is the propagation distance and α is the damping coefficient which can be further represented as (Kim and Lee 2000):

$$\alpha = \frac{\pi\eta}{\lambda}, \tag{8}$$

where η is the loss factor, λ is the wavelength. The loss factor is related to the hysteretic damping ratio of the medium. Given a certain medium, the vibration wave of higher frequency (shorter wavelength) will attenuate faster than that of lower frequency.

3.2 Dispersion

The dispersion (French 1971) is a common phenomenon that is easily found in different kinds of media, but with different underlying physical mechanisms. We can see it happening when white light passes through a prism and is broken down into different colors. The wave velocity of red light in glass is greater than that of blue light.

In general, the dispersion of the mechanical wave we discuss here means different frequency components of a vibration wave travel at different speeds in the medium. As shown in Fig. 3, fingernail tip touch sounds on a wooden table are captured, and the waves with higher frequency (shorter wavelength) arrive earlier than lower ones (Kim 2018).

What is more, the time difference of arrival (TDoA) between two different frequency components is linearly proportional to the propagation distance from the vibration source (denoted as D) as follows:

$$T(f_i) - T(f_j) = D\left(\frac{1}{V(f_i)} - \frac{1}{V(f_j)}\right), \tag{9}$$

where $T(f)$ and $V(f)$ is the arrival time and velocity of vibration at frequency f.

3.3 Body wave and surface wave

The tiny excitation on the physical surface will cause the medium particles to reciprocate near their equilibrium positions and propagate far away in the form of vibrational waves. Vibration waves can be divided into two categories according to the characteristics of the medium particle motion and the wave propagation law; one is the body wave; the other is the surface wave.

Body waves can be divided into longitudinal waves (i.e., primary waves, P-waves) and transverse waves (i.e., Secondary waves, S-waves). P-waves travel along the propagation direction of the vibration waves, causing the compression and dilation of the medium particles. The propagation direction of the S-waves is perpendicular to the vibration waves. This type of wave travels along the surface of the medium at a velocity of about 60–70% of P-waves, but it is more powerful due to its lower energy decay.

Under certain conditions, body waves can form surface waves, which can also be divided into two types, namely, Love waves and Rayleigh waves. When the P-waves and S-wave meet at the medium interface, they interfere with each other and superimpose to produce surface waves. The surface wave has lower frequency but stronger energy, mainly propagating along with the medium interface.[1] The propagation of the Love wave is relatively limited, and it is not easy to observe from the vibration sensor reading. In contrast, the Rayleigh wave makes the synthetic motion of

[1] The medium interface indicates the contact surface of two types of medium, like the surface between air and earth.

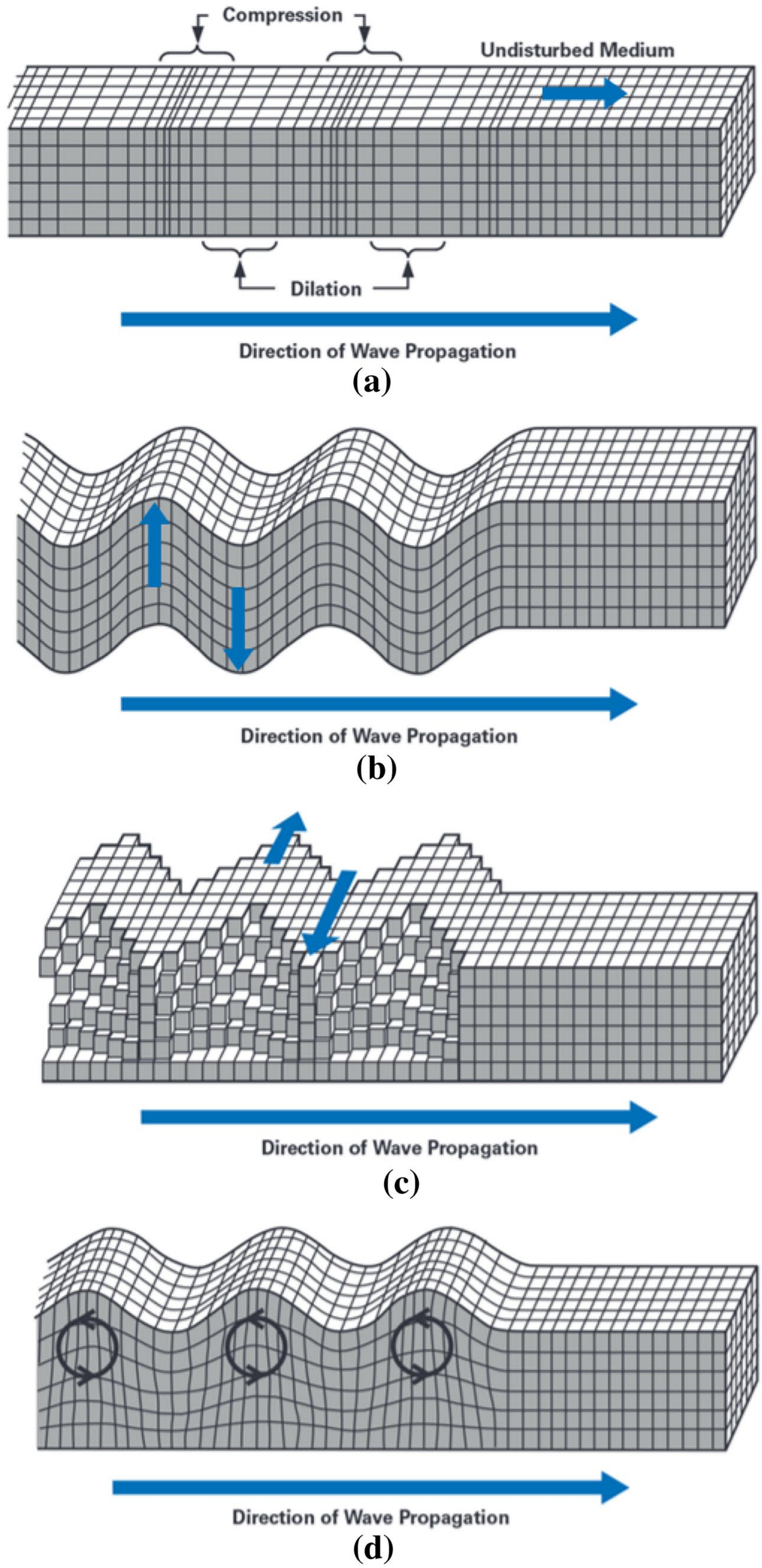

Fig. 3 Four types of vibration waves. **a** Longitudinal wave; **b** transverse wave; **c** love waves; **d** Rayleigh waves (Santos et al. 2019)

Table 1 The comparision of different types of wave in terms of velocity, frequency, decay and power

Wave types	Velocity	Frequency	Decay	Power
P-waves	Fastest	Highest	$\propto$ distance	Weakest
S-waves	Medium	Medium	$\propto$ distance	Medium
Rayleigh waves	Slowest	Lowest	$\propto$ distance$^{1/2}$	Strongest

the medium particles elliptical, resulting in more destructive deformation. As shown in Fig. 3, P-waves, S-waves, and Rayleigh waves are typically selected as the effective waves for vibration wave analysis, and the comparison of the characteristics between them is listed in Table 1.

In the vibration-based sensing applications, the wave propagation characteristics can be leveraged to infer the information in our physical world. For example, an impact-induced vibration, like a finger tap, is dominated by Rayleigh waves. On the other hand, a friction-induced vibration, like a finger swipe, is dominated by S-wave (Pan et at. 2017).

3.4 Vibration inside the human body

The human body is a good example to stand for the composition complexity of the medium. It exhibits diversities among people with different height, weight, and body mass index (BMI). The biodiversity also gives a variety in terms of the size and structure of the skeleton, muscle, and vessel. Our hand, where bone, muscle, fat, and blood vessels crisscross together to form a complex structure, is a good example. All of these intuitive elements of body composition are directly related to the mass, stiffness, and damping of the human body that can be regarded as a mechanical system. Thus, we can apply the SMD model to the human body, either part of it or the whole. What is more, even if two people whose weight, height, and BMI are similar, their underlying tissue composition, such as the ratio of muscle and fat, the bone size, can be quite different (Siri 1956). This insight provides a good possibility that takes the on-body vibration signal as vibro-biometrics for user authentication.

As shown in Figs. 4 and 5, when a finger taps on the skin surface, P-waves and S-waves are generated. S-waves propagate in the form of ripples from the point of excitation and mainly cause displacement of the skin surface. The longitudinal waves mostly travel the soft tissues of the human body inwards, excite the bone, and then generate new P-waves that propagate to the skin surface. Further, the waves with higher frequencies are more readily to propagate through bone than soft tissue, and bone conduction can carry energy over larger distances than that of soft tissue (Harrison et al. 2010).

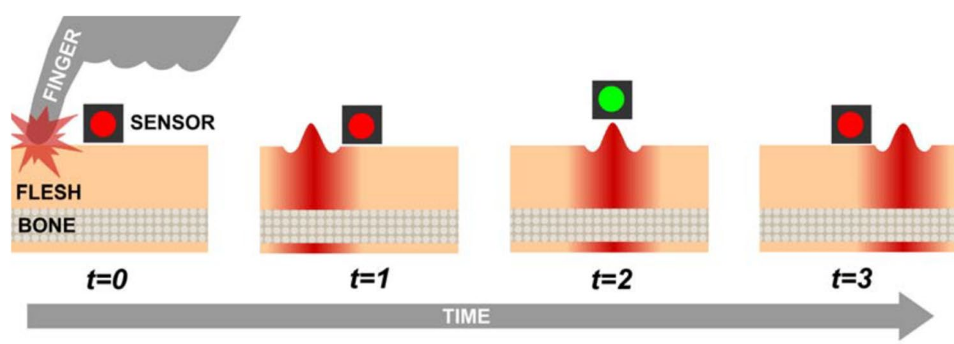

Fig. 4 The transverse wave propagates along the skin surface as ripples (Harrison et al. 2010)

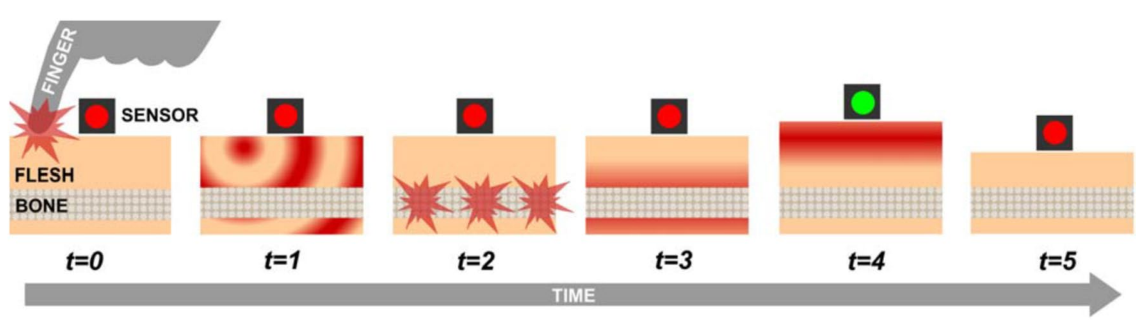

Fig. 5 The longitudinal wave causes internal skeletal structures to vibrate, creating new waves emanate outwards (Harrison et al. 2010)

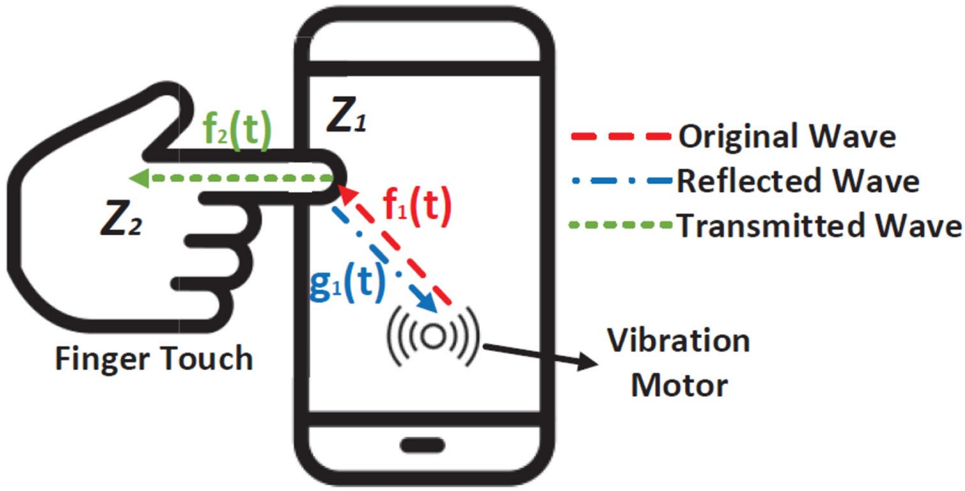

Fig. 6 Illustration of characteristic impedance (Xu et al. 2020)

3.5 Characteristic impedance

The concept of mechanical impedance indicates a measure of how much a system resists the motion subjected to a driving force. This impedance is defined as the ratio of the force to the associated velocity of displacement. It is quite similar to the electrical concept of resistance. The backscatter technique utilizes the property that the radio frequency will be partially reflected when reaching the interface between two mediums with different resistance. When it comes to the vibration wave, similar phenomena occur during the transmission and reflection process, where the original waveform propagates through the contacting area between two different mediums such as the smartphone and the human finger shown in Fig. 6. Given the motor's initial wave generated by the motor, the reflected wave from the finger and the transmitted wave inside the finger are $f_1(t)$, $g_1(t)$, and $f_2(t)$, respectively. By denoting the characteristic impedance of two connected medium as Z_1 and Z_2, we have (French 1971):

$$\begin{cases} g_1(t) = \frac{Z_1 - Z_2}{Z_1 + Z_2} f_1(t) \\ f_2(t) = \frac{2Z_1}{Z_1 + Z_2} f_1(t) \end{cases}. \tag{10}$$

Since the characteristic impedance is mainly determined by the density and material type of the medium, both reflected signal $g_1(t)$ and transmitted signal $f_2(t)$ can be considerably different according to Eq. 10. This provides us a hint that we can collect the reflected signal or transmitted signal that reveals the characteristic impedance and then infer the medium information.

4 Literature review

In this section, we summarize the remarkable literature in the vibration-based sensing area and categorize them into four sub-topics, namely, localization, authentication, health monitoring and communication. In addition, a brief summary of them is provided in Table 2.

4.1 Localization

BOES (Pan 2014) is the first work that develops a geophone prototype and evaluates the coarse-grained localization and occupant counting methods using the footstep vibration at a townhouse. It leveraged the relationship between the signal impulse energy and the impulse-to-sensor distance in Fig. 7 to estimate the footstep location and yielded localization accuracy within 90 cm. Furthermore, as shown in Fig. 8, the system monitors the vibration energy changes in occupancy, which can be inferred as structural information to track the active occupant area.

Then in Mirshekari et al. (2016), the time difference of arrival (TDoA) method is used for locating footstep-induced vibration. This paper focuses more on vibration in the frequency domain rather than in time-domain. The signals are decomposed into frequency components using a Mexican hat wavelet transform, and the components with high energy are selected for accurate trilateration. Some pre-collected footstep samples are used for optimizing the estimated velocity, which can minimize the localization error. The system achieved an average localization error of less than 0.21 m.

Table 2 Summary of existing literature regarding to four sub-topics

Category	References	Description	Application	Methodology	Performance	Sensor
Localization	BOSE (Pan 2014)	Allow sparse sensor configuration for cross-room location-based service	Room-level occupancy detection	Energy-based Estimation	Error: 3 feet fs: 2 kHz	Multiple geophones
	Mirshekari et al. (2016)	Vibration signal is more suitable for indoor localization to some extent because it is much more resilient to the environment interference like multipath	Fine-grained footstep localization	DWT TDoA	Error: 0.21 m fs: 25 kHz	Three geophones
	G-Fall (Huang 2019)	Address the limitation in TDoA-based system that requires a high sampling rate and time resolution	Low-cost footstep localization	Energy-of-arrival (proposed model)	Error: 20 cm fs: 1190 Hz	Three geophones
	Mirshekari et al. (2020)	Floor-vibration-based footstep models are influenced by the structural properties, which may vary from structure to structure	Cross structure sensing Fast and low-effort deployment	Transfer learning SVM	Footstep detection F1-score: 99% across 3 structures	A geophone
	Vibsense (Liu et al. 2017a)	The small screen size restricts the input interaction. Vibsense pushes the limits of vibration-based sensing to locate the tap on any surface	Ubiquitous keystroke recognition on the surface	PSD SVM	accuracy: 97% for 26 keys	A piezoelectric ceramic
	SrufaceVibe (Pan et at. 2017)	Design a vibration-based sensing system that supports the detection of tap location and continuous swipe-track	Ubiquitous surface interaction	Energy-based Sliding Windows TDoA	error(tap): 3 cm error(swipe): 5.8 cm length and 2 degree Area: 40 cm × 40 cm	Four geophones
	Skinput (Harrison et al. 2010)	Turn the skin to be an interaction surface by leveraging the on-body passive vibration	Tap position recognition on the forearm	FFT SVM	Accuracy: 81.5% for 10 locations, 88.8% for 6 locations fs: 55 kHz	Ten piezoelectric ceramics
	Vitype (Chen et al. 2018)	Reduce the sampling rate and the number of vibration receivers for skin interface	Cost-efficient on-body typing system	PSD BPNN	Accuracy: 94.8% for 9 keys fs: 600 Hz	A piezoelectric ceramic
	Taprint (Chen et al. 2019)	Implement the virtual T9 keyboard on the hand back based on the COTS smartwatch	On-body Text Input for COTS Smartwatch	Weighted ASD Fisher Score KNN	Accuracy: 96% for 12 keys fs:500 Hz	A gyroscope and accelerometer

Table 2 (continued)

Category	References	Description	Application	Methodology	Performance	Sensor
Authentication	FootPrintID (Pan et al. 2015)	Extract the gait dynamics from the footstep-induced vibration for user identification to enable smart building applications	Indoor person identification	Regular features in time and frequency domain SVM	Accuracy: 96% for 5 users	A geophone
	VibID (Yang et al. 2016)	Extracted vibro-biometrics from on-body active vibration to enable user identification for wearable devices in small-scale household scenarios	User identification for wearable devices	Temporal features Random Forest	Accuracy: 91% for 8 users	A motor and accelerometer
	Vibwrite (Liu et al. 2017b)	Develop the user authentication via finger inputs on the ubiquitous surface under the active vibration	PIN code and gesture pattern authentication	MFCC and Spectral Point Fisher Score SVM	Accuracy: > 95% within two trials False Positive: < 3%	A motor and piezoelectric ceramic
	Velody (Li et al. 2019)	Defend against replay and synthesis attack in an active vibration-based authentication system	Quick user authentication by putting the hand on a vibrating surface	Cepstral and statistical features One-class KNN	Equal error rate: 5.8% for 15 users	A vibration speaker and accelerometer
	Taprint (Chen et al. 2019)	Utilize the on-body passive vibration generated from finger tap for user authentication on the COTS smartwatch	PIN code and Single-tap authentication for a smartwatch	Weighted ASD Fisher Score DenID	Equal error rate: 2.4% for 128 users	A gyroscope and accelerometer
	Wang et al. (2018)	Vibration patterns of heartbeat cycles can serve as a person's unique identity, and such patterns can be captured by the accelerometers of COTS smartphone for user authentication	Seismocardiogram-based user authentication for smartphone	Cross-correlation DWT SVM	Equal error rate: 2.62% for 20 users	An accelerometer
	TouchPass (Xu et al. 2020)	Reconstruct the vibro-biometric features to be behavior-irrelevant for a more robust user authentication system	Vibro-biometrics based user authentication on a smartphone	CWT + Cepstrum Siamese network Knowledge distillation	FRR: < 4% FAR: < 1.8% 25 participants	A motor and accelerometer

Table 2 (continued)

Category	References	Description	Application	Methodology	Performance	Sensor
Health Monitoring	Fagert et al. (2017)	Understanding human gait balance helps evaluate neurological and musculoskeletal conditions, overall health status and falls risk	Gait balance estimation Footstep force estimation	nonlinear least squares regression	RMSE of footstep force: 61.0 N	A geophone
	G-Fall (Huang 2019)	The state-of-the-art fall detection systems are suffering from serious privacy concerns, having a high false alarm or being cumbersome for users	Indoor fall detection	DWT HMM	Accuracy: 95.74% False alarm rate: $\approx 0\%$	Three geophones
	McCoy et al. (1987)	To study the joints status of both normal and symptomatic subjects by attaching the vibration sensors around the knee	Meniscus injury diagnosis	FFT	Accuracy: 86%	Three accelerometer
	Sharma and Acharya (2018)	VAG signals are useful in quantifying knee-joint status. Early detection and treatment will help to provide a better quality of life for the patients	Abnormal knee-joint identification	OBDLTB-OWFB Log-energy LS-SVM	Accuracy: 89.89%	An accelerometer
	Krecisz and Baczkowicz (2018)	Multiclass classification of different types of knee joint pathology is unknown	Classify five types of knee joint pathology	Statistical, entropy-based, and spectral features Logistic regression	Accuracy: 69%	An accelerometer
	MyoVibe (Mokaya et al. 2015)	Develop a robust skeletal muscle activation detection system, which improves the sports performance and prevents injury	Muscle activation detection	DFT Decision Tree	Accuracy: $>97\%$ (low motion) $>90\%$ (high motion)	Accelerometer network
	Burnout (Mokaya et al. 2016)	Demonstrate the feasibility of using skeletal muscle vibration to help quantify skeletal muscle fatigue in an exercise environment	Quantify skeletal muscle fatigue	R-MPF Regression Tree	Estimation error: $<15\%$	Accelerometer network
	HB-Phone (Jia 2016)	Design an unobtrusive and accurate heartbeat monitoring system that can mount on the bed	Heartbeat monitoring on the bed	ACF	Single person MRE: 1.3% (static) 3.87% (movement)	A geophone
	VitalMon (Jia 2017)	Monitor a person's respiratory rate and heart rate simultaneously, even when the person is sharing a bed with another one	Multi-person vital signs monitoring on the bed	SLD + ACF DUET	Two person MAE: 1.9 beats/min 2.62 breaths/min	Two geophones

Table 2 (continued)

Category	References	Description	Application	Methodology	Performance	Sensor
Communication	OsteoConduct (Zhong 2007)	Leverage acoustic vibration through the human musculoskeletal system to transmit data and interface users in a low-power, secure, non-intrusive way	Body-area data communication	FSK	Data rate: 5 bps Bit error rate: < 10% Power cost: < 1 mW	An electromagnetic shaker and accelerometer
	Ripple (Roy et al. 2015)	Modulate the vibration motors, and decoding them through accelerometers. This paper aims to communicate small packets of information in a secure way	Vibratory communication system	Orthogonal multi-carrier modulation, etc	Data rate: 200 bps Bit error rate: < 1.7%	A vibro-motor and accelerometer
	Ripple II (Roy and Choudhury 2016a)	An improved version of Ripple	Vibratory communication system	New OFDM-based PHY and MAC layers	Data rate: up to 30 Kbps	A vibro-motor and microphone
	(sp)iPhone (Marquardt et al. 2011)	Detect and decode keystrokes by measuring the relative physical position and distance between each vibration	Keystroke eavesdrop	RMS, Skewness, Var, Kurtosis, FFT, MFCC Neural network	Word recovery rate: 80%	An accelerometer
	Gyrophone (Michalevsky et al. 2014)	Show the MEMS gyroscope can measure low-frequency acoustic signals (< 200 Hz). The signals are sufficient to reveal the speaker identity and even parse speech	Speech eavesdrop	MFCC + STFT SVM + GMM + DTW	Speaker Identification: 50% success rate for 10 speakers Speech recognition: 77% for 44 words	A gyroscope
	Accelword (Zhang et al. 2015)	Replace the microphone with an accelerometer for hot word detection in the voice control system to save energy consumption	Hot word detection	Multiple features in time and frequency domain Decision tree	Accuracy: 85% False positive: < 5%	An accelerometer
	VibraPhone (Roy and Choudhury 2016b)	Demonstrate the feasibility of using the vibration motor in mobile devices as a sound sensor. This paper reconstructs the acoustic signals without machine learning	Speech eavesdrop	back-EMF, etc	Accuracy: 80% by human and 60% by software	A vibration motor

Table 2 (continued)

Category	References	Description	Application	Methodology	Performance	Sensor
Others	ViBand (Laput et al. 2016)	Develop a custom smartwatch and sample vibration with an accelerometer at 4 kHz for fine-grained hand gesture recognition	Gesture recognition (passive vibration)	FFT-based features SMO-based SVM	Accuracy: 94.3% for 17 gestures	An accelerometer
	FingerPing (Zhang 2018)	Different hand gesture creates distinct transmission paths from the vibro-motor to the receivers, which enable fine-grained hand gesture recognition	Gesture recognition (active vibration)	35 features SMO-based SVM	Accuracy: 93.77% for 12 phalanges 95.64% for 10 ASL	A vibro-motor and four microphones
	Oinput (Huang et al. 2018)	Deploy vibration sensors on the wrists to collect the keystroke vibration for ubiquitous text input	Keystroke recognition	LSTM	Accuracy: 93.3% for 31 buttons	Two piezoelectric ceramics
	FaceInput (Guan et al. 2019)	Design a text input system based on facial vibration generated from speech for smart glasses, which resists to the on-air speech interference	Voice command input	MFCC HMM	Accuracy: 98.2% for 10 numbers	A piezoelectric ceramic

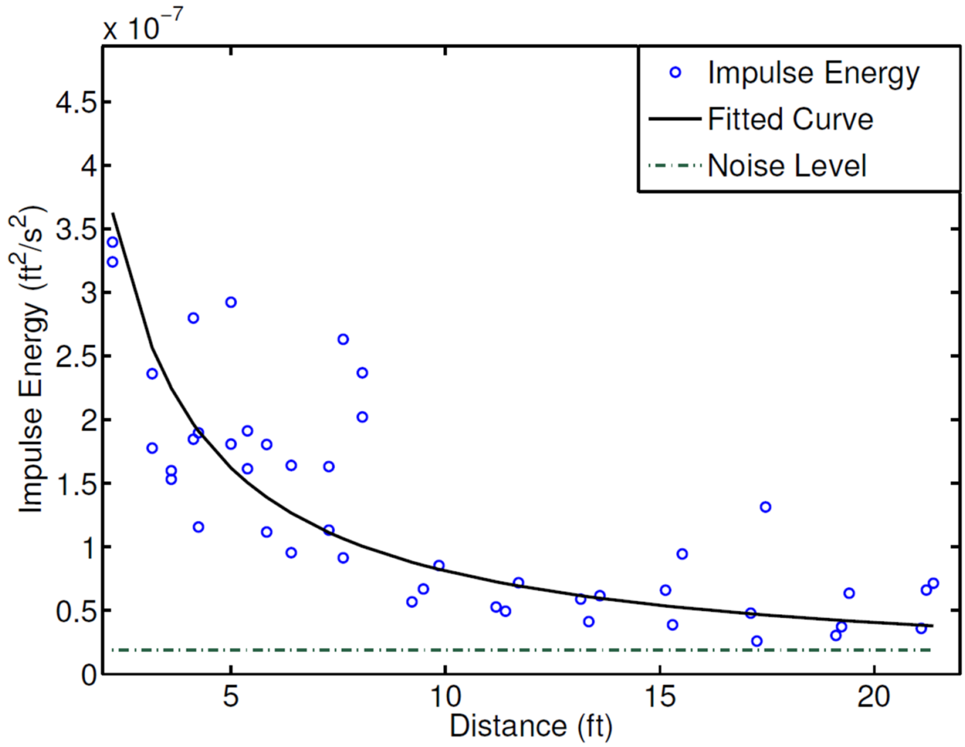

Fig. 7 The relationship between impulse energy and impulse-sensor distance fits the 1/distance decay (Pan 2014)

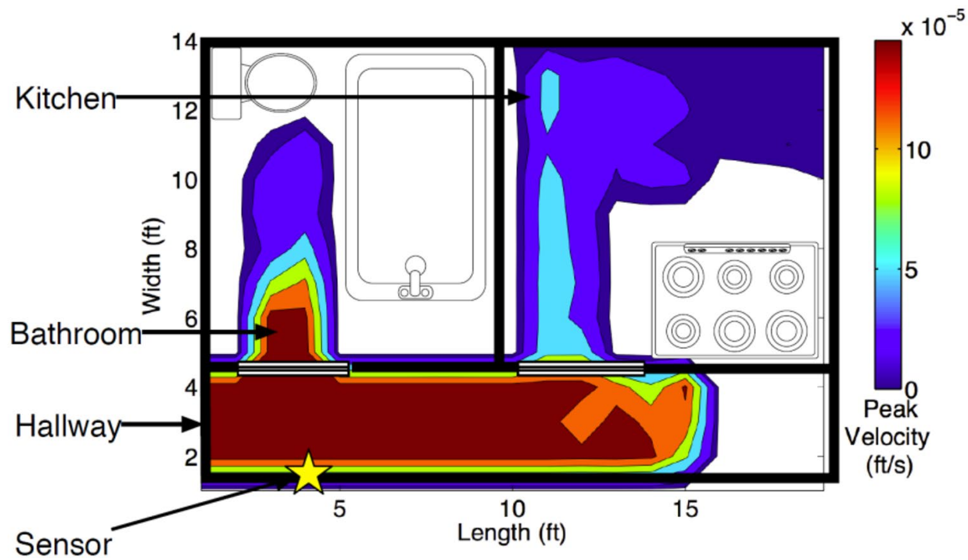

Fig. 8 Impulse responses at a townhouse: Heat map showing vibration signal energy in different regions in a residential townhouse (Pan 2014)

Huang et al. (2019) propose a novel localization algorithm called Energy-of Arrival (EoA), which calculates the arrived energy ratio between geophones. It overcomes the drawbacks of TDoA that require high sampling frequency (e.g., 25KHz in Mirshekari et al. 2016) to estimate the time difference. EoA algorithm no longer needs to estimate or calibrate the wave velocity that is required in the TDoA-based system. The evaluation result shows that an 80-percentile localization error below 24 cm can be achieved using sampling frequency at 1190 Hz.

The work in Mirshekari et al. (2020) enables the floor-vibration-based footstep detection across different structures by model transfer. Previous research has to train a footstep model with supervised learning methods to detect the footstep event. For addressing the effect due to the variation of structural property, this paper use transfer learning to minimize the maximum-mean-discrepancy (MMD) distance between the source and target structures, as shown in Fig. 9. The experiments show that the

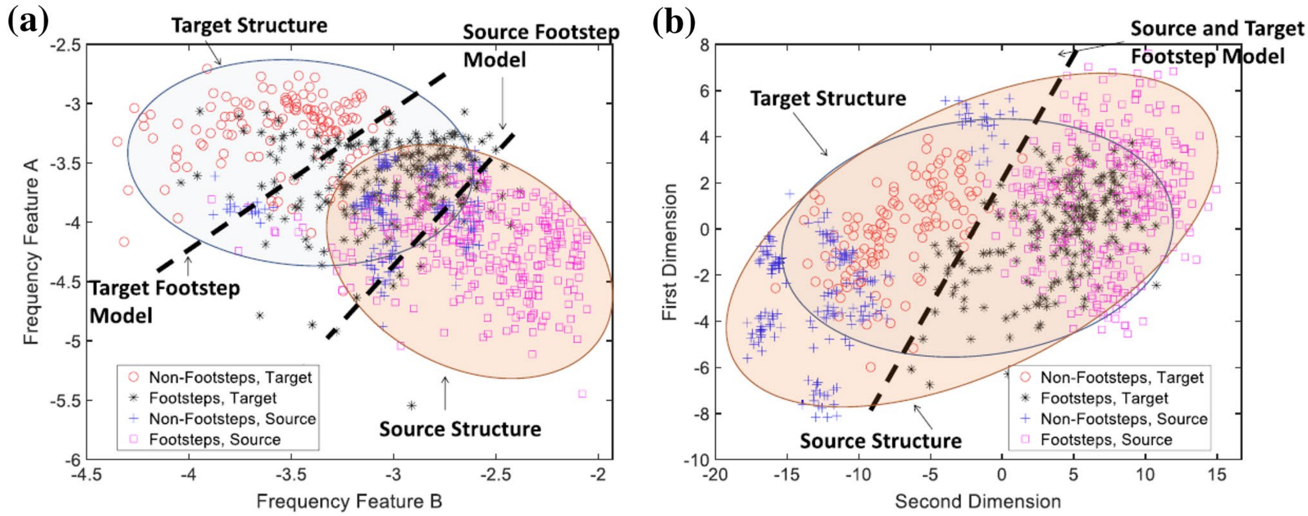

Fig. 9 Part **a** shows the distance between the distributions caused by different structures before projection. Part **b** shows the distributions where the footstep models are aligned after projection (Mirshekari et al. 2020)

proposed approach can detect footsteps across three types of structures with the F1 score of up to 99%.

Vibration-based indoor localization gives new inspiration to the researcher in the area of human–computer interaction (HCI). Not only can they leverage the vibration on the floor, but they can also locate the vibration event on any physical planes. This vision aims to turn all the physical planes into interactive planes for supporting more applications in a smart space.

In Vibsense (Liu et al. 2017a), a ubiquitous keyboard that recognizes the user's keystroke vibration on the table is proposed. The system utilizes a piezoelectric ceramic sensor to collect keystroke vibration signals and extracts the signal characteristics in the frequency domain for training a support vector machine model. The precision and recall of identifying 26 characters is 97% and 96%, respectively. In addition, this work used active chirp signal from 300 Hz to 12 kHz to locate and identify six personal objects (including an empty paper cup, an empty glass cup, a can of coke, a US quarter coin, an apple, and an iPhone 5 s) by matching with the training sample pattern.

Then in SurfaceVibe (Pan et al. 2017), the paper presented a vibration-based interaction system that supports finger tap and swipe on several surface types. This paper suggests that tap induced and swipe induced vibration are dominated by surface and body waves, respectively. It deployed four sensors in the corners of the table to cover a square area with a side length from 40 to 100 cm. Using TDoA methods, the tracking results show that the estimation error of tap location is less than 3 cm, while the baseline performance for swipe shows an average length error greater than 5.8 cm and the average angle errors greater than 2°.

The human body is also a good medium for vibration propagation. Skinput (Harrison et al. 2010) presented the first attempt to turn the hand back into an external interface by embed ten piezoelectric ceramic sensors in the wristband. It divided the hand back into ten areas and maps them to the T9 layout keyboard for keystroke recognition. This fingerprint-based localization system on hand back gives an average classification accuracy of 87.6% for ten keys. Comparing to Skinput, ViType (Chen et al. 2018) further reduced the number of sensors from ten to one, and the sampling frequency from 55 kHz to 600 Hz. By using back-propagation neural networks, the average recognition accuracy in ViType is 94.8%, with the initial training sample of 20 for each key. The vision of above mentioned two papers is to address the dilemma that the smartwatch screen is too small to type on. The authors fulfill this vision in Taprint (Chen et al. 2019), which leverages the accelerometer and gyroscope to collect the tapping vibration. This paper overclocks the sampling frequency from 100 to 500 Hz by modifying the Linux kernel in the smartwatch and achieves a high accuracy of 96% for twelve keys mapped onto the finger knuckles.

4.2 Authentication

Apart from localization, vibration-based authentication is also an appealing research topic that yields many novel and advanced authentication mechanisms. The mechanical vibration that happens in the physical world is highly dynamic. The external excitation from a thing to the floor may vary in terms of the hitting angle, period, mass, etc. Moreover, it is able to extract vibro-biometrics from the on-body vibration signals.

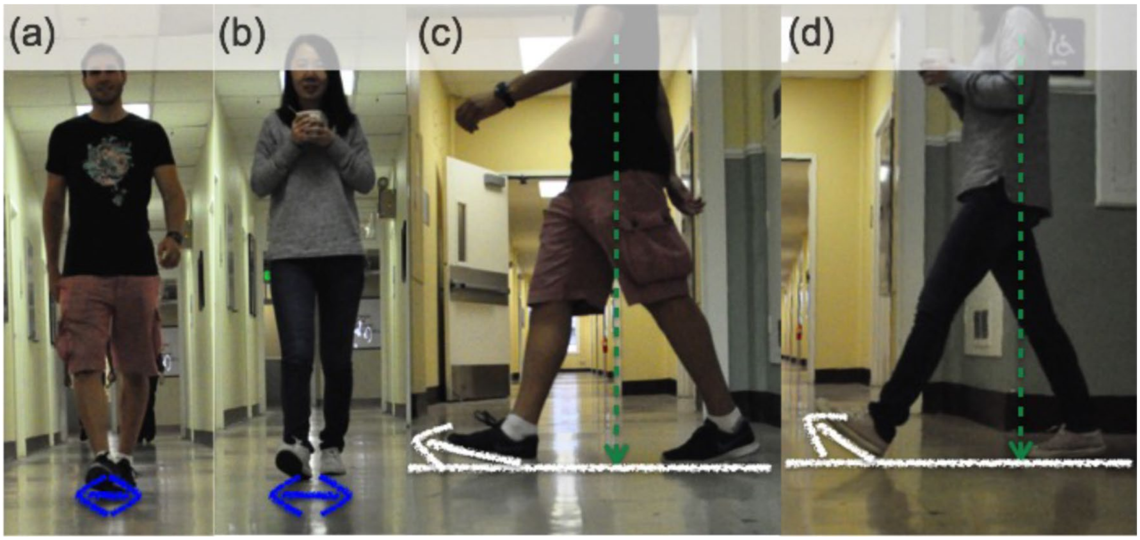

Fig. 10 These figures show two people walking with different gait patterns. **a** and **b** show differences in the distance between two feet. **c** and **d** indicate the differences in the feet-floor angle. The dotted green line also presents the center of gravity variation across different people (Pan et al. 2015)

FootprintID (Pan et al. 2015) presents the first work utilizes the footstep-induced floor vibration to infer the pedestrian gait for user identification. As shown in Fig. 10, the key insight lies in finding how individual footstep vibration signals are changed with respect to the walking speeds, step frequency, step length, and foot–ground angle. By applying an iterative transductive learning algorithm (ITSVM), FootprintID can achieve up to 96% accuracy with limited training data collected by one geophone sensor.

As for authentication using on-body vibration, VibID (Yang et al. 2016) is the first work to validate that the vibration response of the human body reflects the unique physical characteristics of users (i.e., the mass, stiffness, and damping discussed in Sect. 3.4). This system deploys an eccentric rotating mass (ERM) vibration motor on the user's arm to generate active vibration. The receiver, an accelerometer, is embedded in a wristband to collect the on-body vibration response. After the analysis of vibration patterns at different frequencies using the Random Forest algorithm, the system can tell who is using the device in a small-scale scenario of 8 users with an identification accuracy above 91%.

In VibWrite (Liu et al. 2017b), the authors put the active motor on the solid surface to enable user authentication via analyzing the active vibration signal affected by finger gesture (e.g., tapping PIN code and swiping lock pattern on the surface). The proposed prototype can be extended to any solid surface for secure access control, such as access to a room or vehicle. Instead of performing gestures on the vibrating surface, Velody (Li et al. 2019) only requires the users to put one of their hands on the surface to gain access permission. This following work proposes a challenge-response biometric authentication model against the replay attack that is not addressed in VibWrite. As shown in Fig. 11, the authentication service records a large set of challenge-response pairs in advance. The system will play a new challenge when authentication is requested and then discard it after the session. Therefore, by making each challenge-response pair unique and never using it again, the system will not suffer the replay attack.

Since the vibration motor and senor are standard configurations to mobile devices, some works leverage the same characteristic of on-body vibration for user authentication on smartwatch and smartphone.

Chen et al. (2019) exploit tap-induced on-body vibration in the frequency domain and enlarge the difference by weighting the sensitive frequency bins. The users are able to gain quick and secure access into the smartwatch by just a tap on the hand back with one finger. The passive vibration signal samples of 128 participants are input into a density-based one-class classier (termed as DenID), yielding an equal error rate at 2.4%.

Wang et al. (2018) extract the heartbeat biometrics with the built-in accelerometer in a smartphone for user authentication. They leverage the uniqueness of seismocardiogram (SCG), which refers to the vibration of the heartbeat response on the chest. The user attaches the smartphone to his/her chest to collect heartbeat signals. The system is able to identify the user within five heartbeat cycles. The evaluation on 110,000 heartbeat samples from 35 participants shows that the system achieves an equal error rate of 3.51% for user authentication.

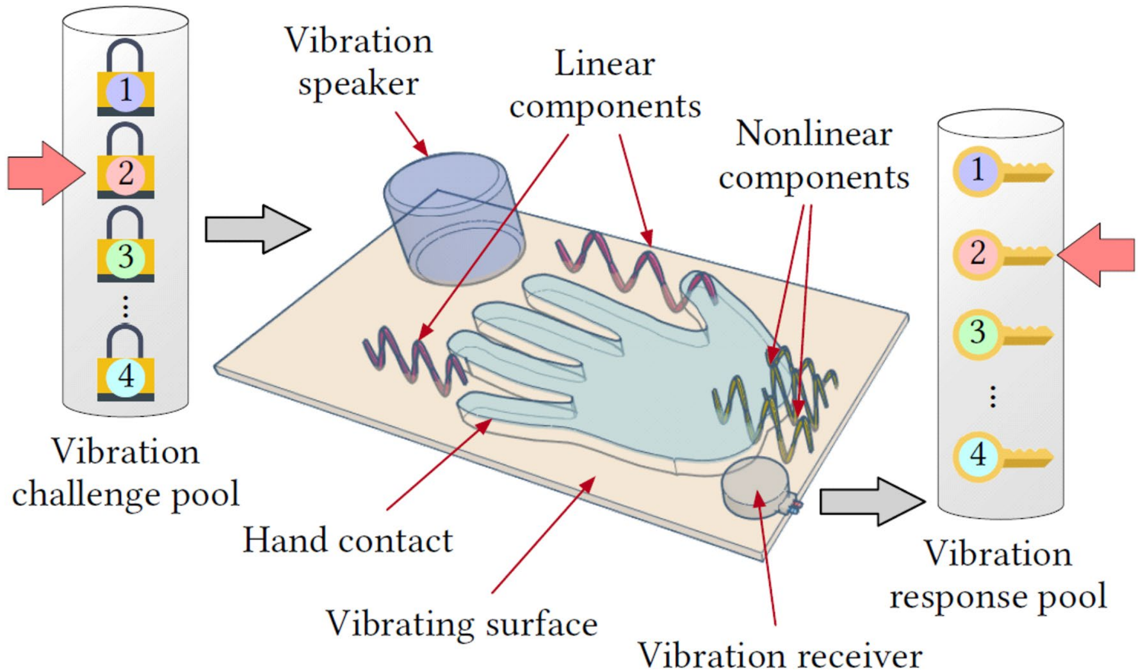

Fig. 11 Illustration of challenge-response biometric authentication in VELODY. The challenge indicates the active vibration from the speaker, and the response indicates the received vibration signals (Li et al. 2019)

TouchPass (Xu et al. 2020) investigates the physical characters of touching fingers on a smartphone generating a 300 ms vibration signal pulse. They designed a Siamese network-based architecture to reconstruct the extracted features to behavior-irrelevant features. To achieve a light-weighted authentication system that can be run on the smartphone in real-time and save more energy, the idea of knowledge distillation is used to compress the network.

4.3 Health monitoring

It is not so intuitive how the vibration signal is related to health monitoring. However, in fact, the body-induced vibration is a good indicator that reflects the body states. For example, we can infer from the ground vibration signal whether the occupant is walking, sitting down, or falling on the ground. Vibration due to body movement can also be used as an auxiliary basis for medical diagnosis. Even the tiny heartbeat vibrations can be monitored and achieve measurements of heart rate and respiratory rate.

Fagert et al. (2017) presented a method for estimating human left/right walking gait balance by collecting and analyzing the footstep vibration. By using sparsely deployed geophone sensors, this method enables gait balance assessment in a non-intrusive way, and it requires no professional healthcare providers. The physical insight is that the vibration wave energy is a function of the footstep force, which can be used to define the gait balance. By studying the gait balance, one can learn their neurological and musculoskeletal conditions, overall health status, and risk of falls.

In addition to predicting the risk of falls in advance, fall detection and alarming are also important. In G-Fall (Huang 2019), a zero false-alarm and training-free automatic fall detection system for the elderly living alone is proposed. Instead of detecting the threshold of the floor vibration signal, it utilizes the hidden Markov model (HMM) to recognize the unique transient state of human fall. The transient state occurs when different parts of the body impact the floor one after another in a short time. With the assistance of energy-of arrival (EoA) localization using three geophone sensors, the system achieves 95.74% recognition accuracy and reduces the false alarm rate to nearly 0%.

McCoy et al. (1987) proposed vibration arthrography, a concept for making the medical diagnosis by analyzing vibration patterns. As shown in Fig. 12, they placed three accelerometer sensors on the patient's knee skin to showed that frequencies with degeneration were generally higher than those found with meniscal injuries. Afterward, there was a lot of following work to diagnosis knee joint pathology using vibration arthrography (Kraft et al. 2019). The dominant approach in most of the work is to analyze the vibration patterns with time-domain, frequency-domain, and statistical features and combine them with a classifier to perform classification.

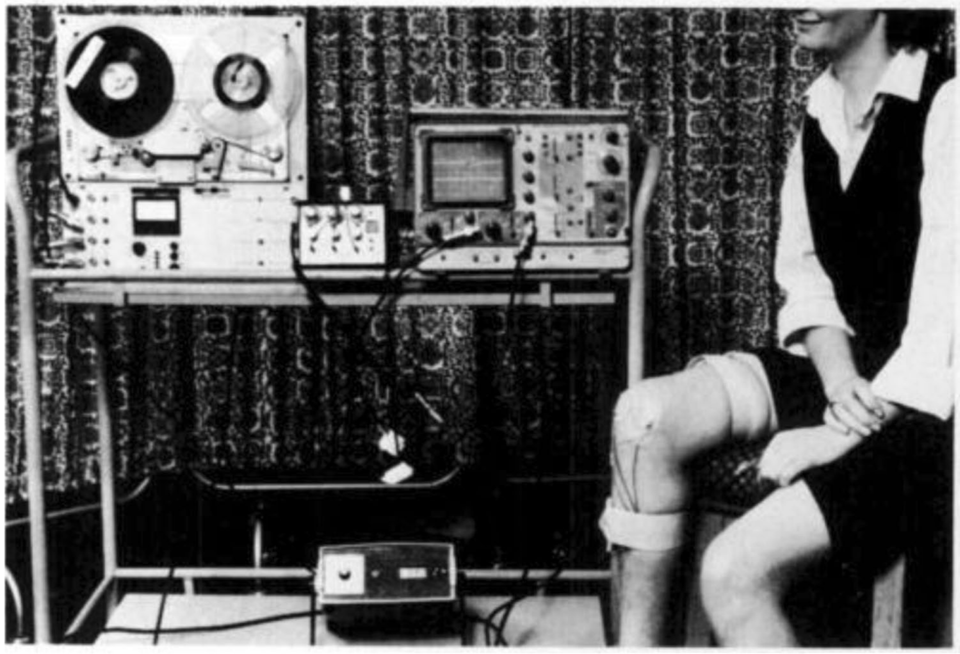

Fig. 12 Subject attached to the recording apparatus for vibration arthrography (McCoy et al. 1987)

In 2018, Sharma and Acharya (2018) chose the optimal bandwidth-duration localized three-band (OBDLTB) orthogonal wavelet filter banks (OWFB) to extract the VAG feature. They obtained a classification accuracy of 89.89% by applying the least-squares support vector machines (LS-SVM). The VAG differentiation between the pathologic states of the knee joint was proved through computer-aided analysis (Wu 2015). Still, most of the researches can only provide the classification result with an accuracy of around 90% between normal and abnormal knees. In Krecisz and Baczkowicz (2018), the authors tried to classify five types of knee joint pathology using statistical, entropy-based, and spectral features with a logistic regression classifier and reported 69% accuracy only.

MyoVibe (Mokaya et al. 2015) presents the first work that recognizes the human muscle activation states during exercises through sensing small muscle vibration. They attach a sensor node network that consists of multiple small form factor accelerometers on the human skin to collect the muscle vibration data. Using the same accelerometer sensor network prototype, the authors in MyoVibe further proposed Burnout (Mokaya et al. 2016), which is able to quantify skeletal muscle fatigue by applying the region mean power frequency (R-MPF) gradient. The R-MPF correlates the muscle vibration data with the ground truth—Dimitrov's spectral fatigue index gradient and provides the user with a quantitative understanding of their skeletal muscle fatigue.

HB-phone (Jia 2016) is the first geophone-based system that can monitor the heartbeat. The bed-mounted geophone has a gain of 200X to detect the tiny heartbeat vibration that travels through the mattress. The systems filter the noise caused by various body movements such as arm swings, leg kicks, and snoring. Then a sample auto-correlation function is applied to extract the periodicity of heartbeats. In the realistic study of 9 subjects, the system generates an average estimation error rate at 8.25% on more than 181 h' data. The authors further improve the bed-mounted geophone system (Jia 2017) and enable the simultaneous detection of the breathing rate and heart rate for two people. Based on the square-law demodulation approach, the median error of the respiratory rate estimation algorithm in this paper is 0.72 beats per minute and 1.95 breaths per minute for heart rate and breath rate, respectively.

4.4 Vibration communication

Compared with the sound signal widely propagating in the air, the vibration signal takes solid as the transmission medium for short-distance transmission and communication, and the propagation range is limited. However, this does not prevent the vibration signal from being an alternative means of communication to the body-area network. To some extent, the proximity of communication guarantees higher security for the low data rate communication between implantable or wearable devices, such as secure device pairing using encrypted vibration signals.

OsteoConduct (Zhong 2007) transmits data through bone conduction and demonstrates the possibility of data transmission at 5 bits/sec between the wrist, ear, and lower back. The measurement shows that the ultra-low-power excitation less than 1 mW is sufficient for relatively reliable communication with a bit error rate of less than 10% without being noticeable to the users.

Ripple (Roy et al. 2015) mounts a vibration motor and accelerometer to a cantilevered metal arm, amplifying the vibration. Through multiple frequency modulation and resonance braking, the system transmits data at around 200 bps. Then the authors push forward the system and release Ripple II (Roy and Choudhury 2016a), which replaces the accelerometer with the microphone as the receiver. By augmenting it with a new PHY/MAC layer, the transmission throughput achieves 150× gain (30 Kbps) than before. Even if the vibration signals attenuate through human tissues and muscles, transmitting data at effective bit rates of 7.41 Kbps is still possible.

The vibration signal propagating along the human body has relatively high security. Still, it is not so lucky for the vibration channel propagating along the physical plane or the air. For example, (sp)iPhone (Marquardt et al. 2011) demonstrate an application that can access the accelerometer readings on mobile phone and then utilize such data to infer the text input on a nearby keyboard. By calculating the relative position and distance between each keystroke vibration, the system can recover 80% input words.

Michalevsky et al. (2014) are the first to present the feasibility that the rotational motions reading of gyroscope in the smartphone can detect the sound signals. Using pattern recognition techniques on the extracted features of signals, the accelerometer reading is also able to classify as spoken keywords such as "Hello Siri" (Zhang et al. 2015). Further, VibraPhone (Roy and Choudhury 2016b), without any training or machine learning algorithms, the recorded signal by a vibro-motor can reveal the whole human speech with an average accuracy greater than 80%. The recovered sound signals can be recognized by off-the-self speech recognition software at 60% accuracy.

4.5 Other vibration sensing applications

ViBand (Laput et al. 2016) utilizes a smartwatch with a sampling frequency at 4000 Hz to detect the vibrations of motor-powered objects grasped by the users. It enables the recognition of 29 pieces of objects, which provides sufficient information to support context-aware service to enhance daily experiences. FingerPing (Zhang 2018) mounts a vibration speaker on the thumb to inject vibration chirps from 20 to 6000 Hz to the hand. When performing a different gesture such as the American Sign Language (ASL) from 1 to 10, the distinct transmission paths from the speaker to four receivers on the wrist can be recognized through a classifier. Similarly, Oinput (Huang et al. 2018) employs two piezoelectric ceramic sensors on the hand back to detect the bone-transmitted signals when a user is typing on a QWERTY keyboard. The system can achieve high-precision keystroke recognition for ubiquitous text input by adapting the anti-noise recurrent neural network. Last but not least, FaceInput (Guan et al. 2019) embeds a piezoelectric ceramic sensor on the glass to collect and recognize the speech vibration. This system addresses the problem that air-borne voice commands will activate other users' smart glasses by mistake.

5 Discussions

5.1 Impact of the environments changes

We mainly discuss the environmental impact to the vibration-based sensing system in two aspects. In the case that vibration signals travel on the indoor floor or physical plane (e.g., table surface), geophone sensors or piezoelectric ceramics sensors are usually the first choices. The amplifier gain is typically set as large as possible to cover a larger sensing range. For example, the effective range for indoor localization using geophone can be a radius of 10 m. There will be many hidden noises are introduced into the system when a specific sensing application is running. The hidden noise sources (Zhang 2019) can come from the human activities (e.g., walking, exercising, closing doors, typing, and so on), indoor system (e.g., vending machines, house refurbishing, water system), outdoor influences (e.g., passing cars, road maintenance, and weather). The intermittent hidden noises will affect the performance of some applications and need to design complex signal processing to deal with them. One the other hand, the on-body vibration source mainly comes from body movement, human speech, and heartbeat. It is easy to filter out those noises because they realize in low frequency.

5.2 Multi-sources sensing

Multi-source sensing has always been a troublesome problem in the field of intelligent sensing. There are some works using CSI of WiFi signals or UWB devices to differentiate and track multiple users simultaneously. Still, these methods depend on the high-cost supports of high-resolution signals, multiple channel/antenna deployment, and large bandwidth. The same problem also exists in intelligent sensing based on the vibration signal. Although one work (Shi et al. 2019) claims that they have realized device-free multiple people localization using geophones, the system can only separate two users' walking tracks. They assume that the floor vibration signal can be visually differentiated from time-domain once the two users' footsteps do not step at the same time. Therefore, in practical usage, it is still infeasible to extract the desired information from the superposition of multiple footstep-induced vibration signals. For the moment, the vibration signal that we get from vibration sensors (e.g., geophone, piezoelectric ceramics, and inertial measurement unit) is of low resolution. The coarse-grained signals result from the intrinsic property of vibration. Typically, the body-induced floor vibration or plane vibration travel at the velocity of 200–300 m/s, and its frequency is mainly around 250 Hz. The wavelength of such vibration is about 1 m, which is inferior to radio frequency (e.g., 2.4 GHz WiFi with wavelength at 12.5 cm.) regarding signal resolution.

5.3 Detection across different structures

The majority of vibration-based sensing application is data-driven because the vibration in the real world is extremely dynamic and complicated. Therefore, it is nearly impossible to model the vibration event and apply the model to solve a specific sensing problem. This situation leads to a dilemma that we have to spend a lot of effort and resources to collect the vibration data and retrain the model when we move the system to a new scene. It is a crucial problem of how we can keep the system performance unchanged across different structures at the algorithm level. In Mirshekari et al. (2016), the authors successfully detect the footstep-induced floor vibration across three types of structures (e.g., wooden, concrete, and metal deck floor with carpet) using transfer learning. However, in reality, the building structure is ever-changing and more than three types, which makes the mapping between source structure space and target structure space trickier. In addition, the on-body vibration signal also exhibits high diversity regarding different body structures. Our previous work (Chen et al. 2019) that locates the finger taps on the hand back is still a fingerprint-based system. How to make this system user-independent (i.e., recognizing the keystrokes on hand back across different users' hand back structure without training) is still an open issue because the transfer learning suffers setbacks when dealing with the high diversity of body structure in our case.

5.4 From data-driven to model-driven

Based on the summary in Table 2, we can find that the overwhelming majority of literature designed their system utilizing traditional machine learning frameworks, e.g., collecting training samples, signal processing, feature extraction, feature selection, and machine learning algorithm. Unlike computer vision, we do not have sufficient data that can cover all the application scenarios. We have to input a lot of effort to initialize the system when we migrate it into a new environment. Although researchers refer to many vibration properties, as mention in Sects. 2 and 3, we can only use those properties to explain why we can realize a specific application. It is still unclear about the quantifiable calculation for a specific result using the vibration model in many cases.

6 Conclusion

In the past 5 years, the emerging vibration-based intelligent sensing has aroused the interest of the researchers. A large variety of novel applications using vibration signals is presented. In this article, we have discussed more than 40 representative literature in this area and classified them into four categories according to their application scenarios. Our survey has shown that vibration property is various and can be applied to a large number of sensing applications. We believe that there still many potential properties waiting to be discovered and leveraged. This is the first survey about vibration-based intelligent sensing, and we hope that it can help new researchers catch up with this area quickly and get some inspirations from this paper.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Abdullah, A., Sichani, E.F.: Experimental study of attenuation coefficient of ultrasonic waves in concrete and plaster. Int. J. Adv. Manuf. Technol. **44**(5), 421–427 (2009)

Chandrakala, S., Jayalakshmi, S.L.: Environmental audio scene and sound event recognition for autonomous surveillance: a survey and comparative studies. ACM Comput. Surv. **52**(63), 1–34 (2019)

Chen, W., Guan, M., Huang, Y., Wang, L., Ruby, R., Hu, W., Wu, K.: ViType: a cost efficient on-body typing system through vibration. In: Proceedings of IEEE SECON (2018)

Chen, W., Chen, L., Huang, Y., Zhang, X., Wang, L., Wu, K.: Taprint: secure text input for commodity smart wristbands. In: Proceedings of ACM MobiCom (2019)

Fagert, J., Mirshekari, M., Pan, S., Zhang, P., Noh, H.Y.: Characterizing left-right gait balance using footstep-induced structural vibrations. In: Proceedings of SPIE (2017)

French, A.P.: Vibrations and waves. CRC Press, Boca Raton (1971)

Guan, M., Chen, W., Huang, Y., Ruby, R., Wu, K.: FaceInput: a hand-free and secure text entry system through facial vibration. In: Proceedings of IEEE SECON (2019)

Harrison, C., Tan, D., Morris, D.: Skinput: appropriating the body as an input surface. In: Proceedings of ACM CHI (2010)

Huang, Y., Cai, S., Wang, L., Wu, K.: Oinput: a bone-conductive QWERTY keyboard recognition for wearable device. In: Proceedings of IEEE ICPADS (2018)

Huang, Y., et al.: G-Fall: device-free and training-free fall detection with geophones. In: Proceedings of IEEE SECON (2019)

Jia, Z. et al.: HB-Phone: a bed-mounted geophone-based heartbeat monitoring system. In: Proceedings of ACM/IEEE IPSN (2016)
Jia, Z. et al.: Monitoring a Person's heart rate and respiratory rate on a shared bed using geophones. In: Proceedings of ACM Sensys (2017)
Kim, H. et al.: UbiTap: Leveraging Acoustic Dispersion for Ubiquitous Touch Interface on Solid Surfaces. In: Proceedings of ACM Sensys (2018)
Kim, D.S., Lee, J.S.: Propagation and attenuation characteristics of various ground vibrations. Soil Dyn. Earthq. Eng. **19**(2), 115–126 (2000)
Kraft, D. et al.: A survey on vibration and sound analysis for disease detection of knee and hip joints. In 6th International Workshop on Sensor-based Activity Recognition and Interaction (2019)
Krecisz, K., Baczkowicz, D.: Analysis and multiclass classification of pathological knee joints using vibroarthrographic signals. Comput. Methods Programs Biomed. **154**, 37–44 (2018)
Laput, G., Xiao, R., Harrison, C.: ViBand: high-fidelity bio-acoustic sensing usiing commodity smartwatch accelerometers. In: Proceedings of ACM UIST (2016)
Li, J., Fawaz, K., Kim, Y.: Velody: nonlinear vibration challenge-response for resilient user authentication. In: Proceedings of ACM CCS (2019)
Liu, J., Chen, Y., Gruteser, M., Wang, Y.: VibSense: sensing touches on ubiquitous surfaces through vibration. In: Proceedings of IEEE SECON (2017a)
Liu, J., Wang, C., Chen, Y., Saxena, N.: VibWrite: towards finger-input authentication on ubiquitous surfaces via physical vibration. In: Proceedings of ACM CCS (2017b)
Liu, J., Liu, H., Chen, Y., Wang, Y., Wang, C.: Wireless sensing for human activity: a survey. IEEE Commun. Surv. Tutor. (2019) **(Early Access)**
Marquardt, P., Verma, A., Carter, H., Traynor, P.: (sp)iphone: decoding vibrations from nearby keyboards using mobile phone accelerometers. In: Proceedings of ACM CCS (2011)
McCoy, G.F., McCrea, J.D., Beverland, D.E., Kernohan, W.G., Mollan, R.A.: Vibration arthrography as a diagnostic aid in diseases of the knee. J. Bone Jt. Surg. **69**(2), 288–293 (1987)
Michalevsky, Y., Boneh, D., Nakibly, G.: Gyrophone: recognizing speech from gyroscope signals. In: Proceedings of SEC (2014)
Mirshekari, M., Pan, S., Zhang, P., Noh, H. Y.: Characterizing wave propagation to improve indoor step-level person localization using floor vibration. In: Proceedings of SPIE (2016)
Mirshekari, M., et al.: Step-level occupant detection across different structures through footstep-induced floor vibration using model transfer. J. Eng. Mech. **146**(3), 04019137 (2020)
Mokaya, F., Lucas, R., Noh, H.Y., Zhang, P.: MyoVibe: vibration based wearable muscle activation detection in high mobility exercises. In: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (2015)
Mokaya, F., Lucas, R., Noa, H. Y., Zhang, P.: Burnout: a wearable system for unobtrusive skeletal muscle fatigue estimation. In: Proceedings of ACM/IEEE IPSN (2016)
Pan, S. et al.: BOES: building occupancy estimation system using sparse ambient vibration monitoring. In: Proceedings of SPIE (2014)
Pan, S. et al.: Indoor person identification through footstep induced structural vibration. In: Proceedings of the International Workshop on Mobile Computing Systems and Applications (2015)
Pan, S. et at.: Surfacevibe: vibration-based tap and swipe tracking on ubiquitous surfaces. In: Proceedings of ACM/IEEE IPSN (2017)
Pathak, P.H., Feng, X., Hu, P., Mohapatra, P.: Visible light communication, networking and sensing: a survey, potential and challenges. IEEE Commun. Surv. Tutor. **17**(4), 2047–2077 (2015)
Rao, S.S.: Mechanical vibrations, 5th edn. Pearson, London (2010)
Roy, N., Choudhury, R.: Ripple II: faster communication through physical vibration. In: Proceedings of NSDI (2016a)
Roy, N., Choudhury, R.R.: Listening through a vibration motor. In: Proceedings of Mobisys (2016b)
Roy, N., Gowda, M., Choudhury, R.: Ripple: communicating through physical vibration. In: Proceedings of NSDI (2015)
Santos, J., Catapang, A.N., Reyta, E.D.: Understanding the fundamentals of earthquake signal sensing networks. J. Analog Dialogue. **53**(3), 41 (2019)
Sharma, M., Acharya, U.R.: Analysis of knee joint vibroarthographic signals using bandwidth-duration localized three-channel filter bank. Comput. Electr. Eng. **72**, 191–202 (2018)
Shi, L. et al.: Device-free multiple people localization through floor vibration. In: Proceedings of the 1st ACM International Workshop on Device-Free Human (2019)
Siri, W.E.: The gross composition of the body. Adv. Biol. Med. Phys. **4**(239–279), 513 (1956)
Wang, L., Huang, K., Sun, K., Wang, W., Tian, C., Xie, L., Gu, Q.: Unlock with your heart: heartbeat-based authentication on commercial mobile phones. In: Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies (2018)
Wang, J., Chang, L., Abari, O., Keshav, S.: Are RFID Sensing Systems Ready for the Real World? In: Proceedings ACM MobiSys (2019)
Wu, Y.: Knee joint vibroarthrographic signal processing and analysis. Springer, New York (2015)
Xu, X., Yu, J., Chen, Y., Hua, Q., Zhu, Y., Chen, Y., Li, M.: TouchPass: towards behavior-irrelevant on-touch user authentication on smartphones leveraging vibrations. In: Proceedings of ACM Mobicom (2020)
Yang, L., Wang, W., Zhang, Q.: VibID: user identification through biovibrometry. In: Proceedings of ACM/IEEE IPSN (2016)
Zhang, L., Pathak, P. H., Wu, M., Zhao, Y., Mohapatra, P.: Accelword: energy efficient hotword detection through accelerometer. In: Proceedings of Mobisys (2015)
Zhang, C. et al.: FingerPing: recognizing fine-grained hand poses using active acoustic on-body sensing. In: Proceedings of ACM CHI (2018)
Zhang, P., et al.: Structures as sensors: indirect sensing for inferring users and environments. Computer. **52**(10), 84–88 (2019)
Zhong, L. et al.: OsteoConduct: wireless body-area communication based on bone conduction. In: Proceedings of BodyNets (2007)

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