Ubiquitous Acoustic Sensing on Commodity IoT Devices: A Survey

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Abstract—With the proliferation of Internet-of-Things devices, acoustic sensing attracts much attention in recent years. It exploits acoustic transceivers such as microphones and speakers beyond their primary functions, namely recording and playing, to enable novel applications and new user experiences. In this paper, we present the first systematic survey of recent advances in active acoustic sensing using commodity hardware with a frequency range below 24kHz. We propose a general framework that categorizes main building blocks of acoustic sensing systems. This framework encompasses three layers, i.e., physical layer, core technique layer, and application layer. The physical layer includes basic hardware components, acoustic platforms as well as the air-borne and structure-borne channel characteristics. The core technique layer encompasses key mechanisms to generate acoustic signals (waveforms) and to extract useful temporal, spatial and spectral information from received signals. The application layer builds upon the functions offered by the core techniques to realize different acoustic sensing applications. We highlight unique challenges due to the limitations of physical devices and acoustic channels and how they are mitigated or overcame by core processing techniques and application-specific solutions. Finally, research opportunities and future directions are discussed to spawn further in-depth investigation on acoustic sensing.

Index Terms—Acoustic sensing, aerial acoustic communication, temporal feature, channel profile.

I. INTRODUCTION

Internet of Things (IoT) [137] technologies enable everyday objects to connect and communicate with each other by augmenting them with sensing, processing, and computation units. With the ever increasing computation power and rich built-in sensors available in IoT devices, novel applications emerge by repurposing sensors beyond their primary use. For instance, cameras are intended for taking photos but have been utilized in visible light communication [136]. Gyroscope and accelerometer sensors are designed for attitude estimation but have been used extensively in activity recognition [67]. WiFi signals, originally used for communication, have been widely applied in many context-aware computing applications including localization [13], [56], [116] and gesture recognition [95], [121]. In this paper, we target innovative sensing mechanisms that exploit acoustic front-ends on commodity IoT devices.

Acoustic front-ends, namely microphones and speakers, are among the most commonly used transducers in IoT devices. They are generally designed for playing back and recording audio signals, but also play a pivotal role in passive sensing applications such as speech recognition [15], [106] and acoustic source localization [25], [97]. Novel active sensing mechanisms that treat acoustic front-ends as transceivers to emit and capture wireless signals have gained a lot interests in the research community. For instance, acoustic signals have been used to establish aerial acoustic communication channels to transmit a small amount of information [50], [62], [84], [120]. Also, the reflective property of acoustic signals have enabled the development of acoustic short-range radars for floor map reconstruction [148] and gesture recognition [87],

![Fig. 1: A general framework for acoustic sensing.](image-url)
Moreover, the relatively slow propagation speed of acoustic waves (comparatively, e.g., Radio Frequency or RF) in common media allows to achieve comparable performance using a relatively low bandwidth than those with RF technologies. Consequently, it is possible to achieve Time-of-Flight estimations that further support many context-aware applications [92], [115], [60], [61], [68], [70], [123]. Last but not least, active acoustic sensing can enable deformity detection and estimation of non-acoustic emitting objects by transmitting purposefully modulated acoustic signals and make inference based on the reflected waveforms captured by microphones [43], [52].

Despite tremendous efforts in developing acoustic sensing applications in the past decade, a systematic treatment of fundamental principles, key design considerations, and innovative methodologies is still missing. As a result, when developing applications based on acoustic sensing, researchers and developers often have to start from scratch and reinvent the wheel. In this paper, we provide the first systematic survey on recent advances in acoustic sensing with emphasis on novel sensing approaches on commodity hardware (with a bandwidth below 24 kHz), as opposed to those that require special-purposed hardware such as underwater acoustic communication or ultrasonic sensing. We review the relevant research in a bottom-up manner, from the physical layer, core technique layer, and application layer, as shown in Fig. 1. The physical layer includes basic hardware components, acoustic platforms as well as the air-borne and structure-borne channel characteristics. The core technique layer encompasses key mechanisms to generate acoustic signals (waveforms) and to extract useful temporal, spatial and spectral information from received signals. The application layer builds upon the functions offered by the core techniques to realize different acoustic sensing applications. We group acoustic sensing applications into aerial acoustic communication, applications leveraging temporal features such as ranging, acoustic radar, acoustic localization and tracking, applications enabled by estimating acoustic channel characteristics such as gesture recognition, speaker liveliness detection and interactive controls. We highlight unique challenges due to the limitations of physical devices and acoustic channels and how they are mitigated or overcame by core processing techniques and application-specific solutions. Along each category of applications, we discuss research opportunities for future investigation. Finally, we summarize under-investigated areas and emerging applications in acoustic sensing as a whole.

The remainder of this paper is organized as follows. In Section II, we introduce typical hardware components and system supports offered by commodity devices and the properties of acoustic channels. In Section III, we present the core techniques to generate acoustic signals and to extract temporal and channel features from received signals. In Section IV, a variety of applications are discussed in details according to the core techniques on which they are based; we discuss research opportunities for each category separately and present future directions in Section V. Finally, we conclude the paper in Section VI.

II. Acoustic Devices and Channels

On an acoustic-enabled device, applications inject processed digital signals to its acoustic frontend (e.g., speakers), which transmits analog acoustic signals through air-borne or structure-borne channels. Upon reception at the acoustic frontend (e.g., microphones) of a receiver device, the analog signals are transformed to digital signals for further processing and are eventually delivered to an application. During the process, extra latency due to processing and system delays, distortions from acoustic frontends and channels and noise and inferences from on-board circuits or environments are introduced. In this section, we present the physical components of acoustic active sensing pipelines and their characteristics. The limitations of acoustic hardware and systems as well as channels pose non-trivial challenges to acoustic signal processing and application development.

A. Acoustic Hardware

The typical pipelines of sound recording and playback systems are shown in Fig. 2(a) and (b) on the transmitter and receiver sides, respectively. The former converts mechanical (acoustic) waves into digital samples while the latter reverses this process. In a recording system, acoustic signals are first converted into voltage signals by a microphone. An Automatic Gain Control (AGC) or Programmable Gain Amplifier (PGA) then amplifies the voltage signals to fit the dynamic range of a posterior Analog-to-Digital Converter (ADC); this helps to improve the digitization resolution and to avoid saturation [2]. Amplified signals further go through a Low Pass Filter (LPF), also known as an anti-aliasing filter, and become band-limited signals. The cut-off frequency of the LPF is $f_s/2$, where $f_s$ is the sampling rate. Filtered signals are finally converted to digital samples by an ADC. A sound playback system reverses the above process. Digital samples are first interpolated and then fed into a Digital-to-Analog Converter (DAC) to become analog signals. The analog signals are further amplified and finally converted to acoustic waves by a speaker.

Contemporary commodity devices often include more than one microphone and one speaker. For instance, modern smartphones utilize two speakers to play stereo audio and employ two microphones to enhance recording qualities. The typical layouts of microphones and speakers on smartphones are shown in Fig. 3. The physical layouts of microphones and speakers are important considerations in some applications, which we defer to Section IV for more detailed discussion.

On acoustic playback systems, amplification or gains of sounds can often be configured. High-power speakers are utilized in applications that operate at long ranges. The most important parameters for acoustic recording systems include sampling rate, bit resolution, and the number of channels (or microphones). The higher the sampling rate and bit resolution, the better the signal quality. The sampling rate typically ranges from 8 kHz to 44.1 kHz, but certain devices (e.g., high-end smartphones) have a maximum sampling rate of 192 kHz [8]. The most common configuration for bit resolution is 8-bit or 16-bit, but customized devices may support a maximum of 32-bit. Whereas higher bit resolutions are generally preferred...
to preserves more signal details, choosing a suitable sampling rate and making use of the two channels commonly available to both sound playback and recording systems have a profound impact on the sensing performance and are further discussed in Section IV-B5.

The acoustic hardware on commodity devices often introduce non-flat frequency response on its input signals. The non-flat frequency response, also known as frequency selectivity, describes a phenomenon where acoustic signals experience different channel gains at different frequencies. This can be problematic for signals that occupy a relative wide frequency range. On the receive side, signals whose bandwidth is below 8 kHz [84], [148] can have a higher receiver gain while those above experience sharp attenuation since microphones on commodity devices are designed primarily for recording human voices. On the transmitter side, with speaker diaphragm inertia [1], introduced by a non-electronic component (diaphragm) in speakers, the movement of speaker diaphragms cannot catch up with fast changes in input signals. Thus, higher frequency signals tend to be dampened. Additionally, it causes ringing effects [62] or frequency leakage [114].

Ringing effects describe the problem in the time domain where a transmission has a delayed start and/or a prolonged transmission duration. In contrast, frequency leakage describes the problem in frequency domain where a transmission of a band-limited signal can cause out-of-band artifacts. As a result, speaker diaphragm inertia can generate audible noise even when the transmitted signal only occupies inaudible frequency bands.\(^1\)

### B. Acoustic Channel Properties

As acoustic signals generated by mechanical vibrations can propagate through both air, liquid, and solid medium, we next discuss the properties of two channels, i.e., air and solid medium that are relevant to acoustic sensing on commodity devices. The acoustic signals propagate through air and solid medium are called Air-borne Signals (AS) and Structure-borne Signals (SS), respectively.

\(^1\)Though the audio range falls between 20 Hz and 20 kHz, most people normally do not hear sounds about 18 kHz [16], [52], [74]. Therefore, the frequency range between 18 and 20 kHz are often deemed inaudible and hence commonly used for acoustic communication and sensing.

1) **Characteristics of Air Channels:** When acoustic signals propagate through air, they radiate their energy spherically towards surroundings and can be deemed as “wireless signals”. Hence, they share many similar features as radio signals. Specifically, acoustic signals experience path loss, Doppler effects, reflection, refraction, and Diffraction.

- **Path Loss:** Path loss describes the phenomenon that the energy of acoustic signals decrease over the propagation distance. Specifically, the acoustic intensity, measured as the ratio between power and area, is inversely proportional to the square of distance [11]. Supposing the intensity of a particular acoustic signal is denoted by \( p \), then a free-space path loss model is given by [11]:

\[
p = k \frac{p_0}{r^2},
\]

where \( k \) is a coefficient, \( p_0 \) is the intensity when distance

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![Sound recording system](image1)

(a) Sound recording system.

![Sound playback system](image2)

(b) Sound playback system.

Fig. 2: Diagrams for typical acoustic hardware.
to the source is \( r = 0 \).

- **Doppler Effects:** Doppler Effect refers to the change in wave frequency during the relative motion between an acoustic source and its receiver (or observer). In particular, the Doppler shift in frequency is given by [6]:

\[
\Delta f = \frac{\Delta v_d}{c} f,
\]

where \( f \) is the original frequency, \( \Delta v_d \) denotes the relative speed between the transmitter and the receiver, and \( c \) is the speed of sound in air.

- **Temperature Effect:** Unlikely RF waves, the propagation speed of acoustic signals is temperature dependent given by [51]:

\[
c = \sqrt{403T_p (1 + 0.32 e/\rho)},
\]

where \( c \) is the sound speed (m/s) in air, \( T_p \) is the temperature (in Kelvin), \( e \) is the vapor pressure of water in air, \( \rho \) is the absolute atmospheric pressure. From Eqn. (3), we see that sound speed is also dependent on humidity. However, since \( e/\rho \) tends to be quite small, Eqn. (3) can be further simplified as \( c^2 = 403T_p \).

- **Reflection, Refraction, and Diffraction:** Reflection means that when an acoustic signal hits a boundary of two different mediums, it will be reflected back. The amount of reflected signals depends on the level of difference between the two mediums. Reflections from solid surfaces in the environments contribute to multipath effects. Refraction happens when a fraction of acoustic signals propagate into another medium and change their direction. Diffraction involves a change in direction of waves as they pass through an opening or around a barrier in their path. This happens when obstacles are smaller than the wavelength of the wave.

2) **Solid Medium Property:** Acoustic signals in solid medium exhibit much differences with those in air. Next, we highlight two key properties within solid medium, namely, acoustic dispersion and resonance.

- **Acoustic Dispersion:** As an acoustic signal containing a rich set of frequency components propagates in a solid medium, high frequency components travel faster than low frequency ones. The speed \( c_f \) of a specific frequency component \( f \) is given by [100]:

\[
c_f = \sqrt{\frac{E h f^2}{12 \rho (1 - v_p^2)}},
\]

where \( v_p \) is the phase velocity, and \( E, \rho, h \) are constants that characterize a medium: \( E \) quantifies elasticity, \( \rho \) characterizes stiffness, and \( h \) represents thickness. Fig. 4 shows the signal recorded by an earbud when a person taps her teeth and generates a pulse vibration that travels through her jaw and skull bones.

- **Acoustic Resonance:** Acoustic resonance describe the phenomenon that a solid medium selectively amplifies a particular frequency component while attenuating other ones. This particular frequency is called resonant frequency, which changes if the properties or the state of the solid medium differs, say, under external forces or undergoing shape transformations.

Besides the afore-mentioned difference, acoustic wave propagation in air and solid medium also differ in speed. The speed of AS is 340 m/s (at temperature of 25°C) and for SS, the speed can be over 2000 m/s (depending on the type of medium) [52]. Interestingly, an acoustic event can generate both AS and SS at the same time. SS appears ahead of the AS in the captured signals if a receiver is in contact with the surface that vibrates and generates the acoustic event. However, depending on the degree of coupling, with the same sensing device, the signal intensity of SS tends to be significantly lower than AS.

C. **Acoustic Platforms**

Due to the pervasiveness of acoustic transducers and IoT devices, platforms that support acoustic operations are diverse, ranging from customized embedded devices and wearables to general-purpose smartphones and laptops. On general-purpose devices, which reply on commodity operating systems (OS) such as Windows, Linux, Android, MacOS and iOS, acoustic applications are subject to limitations of available application programming interfaces (API) and need to contend with other applications or system services in resources.

Different platforms have their advantages and disadvantages in developing acoustic sensing solutions. Platforms running Windows and Linux offer a wide range of software utilities that allow developers to focus on algorithm design and hence facilitate fast prototyping [112]. To capture and playback acoustic signals, one can either use existing software utilities such as Audacity [3] for offline processing or directly deal with raw samples using platform-dependent APIs [4]. However, systems running these OSs tend to be less portable. In contrast, mobile and wearable devices powered by Android or iOS platforms offer native acoustic APIs and are convenient for carrying out various experiments in both indoor and outdoor settings. General-purpose OSs can introduce uncontrollable system delays (in tens of millisecond), missing acoustic samples (e.g., due to insufficient buffers) and “distortions”, say dynamic gains hence inconsistent acoustic fingerprints, as the result of automatic gain control [112], [53]. These artifacts should be taken in account or compensated in developing acoustic solutions. Lastly, customized embedded platforms using commodity hardware components generally allow flexible
physical layer configuration, including increasing the number of channels and tuning hardware properties [18]. Platform diversity implies that it difficult if not impossible to have one-size-fit-all solutions. When porting applications from one platform to another [114], one also needs to devise calibration procedures to mitigate such diversity.

D. Challenges

The characteristics of acoustic hardware, channels and platforms are key design considerations in acoustic sensing solutions. Combating the imperfection and limitations of physical layers requires addressing the following challenges:

- Frequency selectivity caused by acoustic transducers and channels unavoidably results in signal distortions that affect system performance.

  **Challenge I:** Handling frequency selectivity induced signal distortions.

  Various compensation approaches can be applied to flatten the frequency response. More details on this are presented in Section III-C1.

- Speaker diaphragm inertia mentioned in Section II-B may cause disruptive audible noise even if the modulated signal is in inaudible frequency ranges.

  **Challenge II:** Suppressing audible noise incurred by acoustic transmissions.

  Maintaining smooth amplitude and phase transitions between each sample is crucial to mitigate this problem and more relevant techniques will be elaborated in Section IV-B4 and Section IV-C3.

- As explained in Section II-C, the uncertain system delay in response to software signaling can be detrimental to the extraction of temporal characteristics.

  **Challenge III:** Masking the uncertainty system delay for the upper layer functionalities.

  Designing algorithms that are agnostic to system delay may be potential approaches and more discussions on this can be found in Section III-B2 and III-B3.

- Though most acoustic devices share the similar hardware pipeline (Fig. 2), the diversity in both acoustic front-ends and software platforms can pose challenges to application deployment.

  **Challenge IV:** Reducing or eliminating laborious device-dependent calibration when developing acoustic applications.

  Tackling this challenge may require certain level of platform homogenization, and more discussions can be found in Section IV-C.

III. Core Acoustic Sensing Techniques

In this section, we present core techniques for acoustic sensing. These techniques mitigate some of the challenges discussed earlier and serve as building blocks for various applications. Waveform design for sensing and communication is first introduced, followed by mechanisms extracting temporal and frequency domain characteristics.

A. Waveform Design

Waveform design is critical for acoustic sensing systems. We draw a distinction between sensing and communication as the designs suitable for them (albeit related) can be rather different. The available bandwidth for transmitted acoustic waveforms normally goes up to 24 kHz. The frequency range from 20 Hz to 18 kHz is audible to human but has better channel gains in commodity acoustic front-ends [52], while the inaudible range from 18 to 24 kHz, is preferred due to less interference but is subject to sharp attenuation.

1) Waveforms for Active Sensing: The most commonly used signals for sensing include Pure Tone, Frequency Hopping Spectrum Spread (FHSS), and Chirp. Their respective advantages, disadvantages, and suitable applications have been summarized in TABLE I.

   a) **Pure Tone Signals:** Pure tone signals are commonly used in acoustic sensing due to their low complexity and high resolutions in tracking Doppler shifts. Their waveform is represented as $s(t) = \cos(2\pi ft + \phi)$ where $f$ and $\phi$ are the frequency and the initial phase. The waveform and its Short Time Fourier Transform (STFT) spectrogram of a single tone signal are shown in Fig. 5(a) and 5(b), respectively.

   Consider that a moving target transmits a pure tone signal with frequency $f$, and the detected Doppler frequency is $f_{\text{shifted}}$ at the receiver side. The relative moving speed can thus be estimated as $v = \frac{2f_{\text{shifted}}c}{f}$, where $c$ is the sound speed. Due to the low propagation speed of sound, it is feasible to achieve a cm/s-level estimation accuracy. Moreover, if phase components across multiple pure tones are available, the phase diversity yields multiple constraints to obtain more accurate phase and frequency estimations [66], [38]. As phase and frequency shifts are correlated with spatial quantities such as range and speed, pure tone signals have been extensively used in localization and tracking applications [116], [122], [141], [74], as well as gesture recognition [43], [122]. However, they are not suitable for extracting precise timing information due to the periodicity and shallow peaks of auto-correlation functions.

| Waveform          | Advantages                             | Disadvantages       | Suitable applications                  |
|-------------------|----------------------------------------|---------------------|----------------------------------------|
| Pure tone         | Doppler-aware, Responsive, less computational requirements | Vulnerable to interference | Gesture recognition/tracking (relatively short range) |
| FHSS modulated    | less correlation sidelobes, good multipath resolution | Sensitive to noise | Gesture tracking (relatively short range) |
| Chirp             | Noise-resilient, multipath resilient   | Computation intensive | Ranging, localization, radar (relatively long range) |

TABLE I: Comparison of different waveforms designs for sensing purpose.
b) **FHSS Signals:** FHSS modulation rapidly changes the carrier frequency among many distinct frequencies occupying a large spectral band. The changes are controlled by a code or a spreading sequence. The key design consideration of FHSS modulation is to choose an appropriate orthogonal sequence. Commonly used ones for acoustic applications include Zadoff-Chu (ZC) [110], [42], [41], [47], Barker code [52], GSM training sequence [142], and m-sequence [146]. A baseband ZC signal and its STFT spectrogram after modulation are shown in Fig. 5(c) and 5(d), respectively. Thanks to the use of spectrum spreading sequences, correlating FHSS modulated signals results in sharper peaks and smaller sidelobes compared to pure tone or even chirp signals [52], making multiple acoustic reflections readily distinguishable. Therefore, FHSS modulated signals are a popular choice for high-accuracy gesture tracking [52], [142]. Unfortunately, due to their high sensitivity, they can be easily corrupted by channel noises including path loss, the Doppler effect, background interference, etc, making them only suitable for short-range sensing.

c) **Chirp Signals:** A chirp is a signal in which the frequency increases (up-chirp) or decreases (down-chirp) with time. A linear chirp is represented by

\[ s(t) = A \cos \left( 2\pi \left( f_{\text{min}} + \frac{k}{T} t \right) + \phi \right) \]

where \( f_{\text{min}} \) is the initial frequency, \( A \) is the maximum amplitude, \( \phi \) is the initial phase, and \( k = \frac{B}{T} \) is the modulation coefficient or chirp rate [50], [92], [105], [148]. In sensing, chirp signals are transmitted repeatedly, and thus they are also known as Frequency Modulated Continuous Wave (FMCW). The time and frequency domain representations of a chirp signal are shown in Fig. 5(e) and 5(f), respectively. Auto-correlating chirp signals results in sharp and narrow peaks with 3dB temporal bandwidth inverse proportional to the signal bandwidth, a property also known as pulse compression. Since the energy of a signal does not change during pulse compression, concentration of its signal power within a narrow interval leads to a peak SNR gain proportional to the product of signal bandwidth (B) and duration (T) [60]. As a result, acoustic sensing systems employing chirp signals enjoy three major advantages. First, chirp signals are robust to dynamic channel conditions such as Doppler effects. Second, they are detectable even when the signal power is under noise floor [50], and thus can combat strong background noise or interference. Third, chirp signals are resilient to multipath fading, allowing extraction of multipath components [77]. Thanks to these desirable features, chirp signals have been widely used as a building block in temporal feature extraction [74], [77] and channel characteristics estimation [90], [114], as discussed in more details in Section III-B and III-C.

2) **Waveforms for Communication:** The aforementioned waveforms are applicable to aerial acoustic communications as well but different signal configurations (e.g., frequency, spread sequence or chirp rate) represent different source symbols. A comparison of these waveforms and their suitable applications in communication can be found in TABLE II. Commonly used modulations in acoustic communication include Frequency Shift Keying (FSK), Orthogonal Frequency Division Multiplexing (OFDM), and Chirp Spread Spectrum (CSS).

   a) **FSK:** As the amplitude and phases of acoustic signals are prone to channel distortions, modulation techniques based on these two features (e.g., Amplitude Shift Keying or Phase Shifted Keying) are not reliable [62]. In contrast, FSK, a modulation technique that uses pure tone signals with distinct frequencies to represent data bits, is more robust to channel distortion and interference. It can be demodulated via FFT analysis, Hilbert Transform, or coherent detection. Though FSK has low complexity in both modulation and demodulation design, its achievable data rates are low [71].

| Waveform      | Advantages                      | Disadvantages                     | Suitable applications       |
|---------------|---------------------------------|-----------------------------------|-----------------------------|
| Pure tone,   | High data rate                  | Short communication range, high   | Near field communication    |
| FHSS modulated|                                 | BER                               |                             |
| Chirp         | Noise-resilient, multipath resilient, long communication range, low BER | Low data rate               | Long-range, low-volume, strong interference |

TABLE II: Comparison of different waveforms for communication.
b) **OFDM**: Compared to single-carrier FSK, OFDM is theoretically more efficient by modulating data symbols on multiple orthogonal subcarriers. It has the potential to achieve a higher throughput under the same bandwidth [46], [23]. However, when implemented in software for acoustic communication, its advantage cannot be fully realized. Specifically, advanced processing modules such as carrier sensing and carrier frequency offset correction, which are common in RF-based OFDM systems, require hardware level modification due to tight timing requirements. Moreover, as OFDM only maps bit streams onto individual subcarriers, a separate modulation scheme is needed to encode these bit streams. High-order modulations such as Quadrature Amplitude Modulation (QAM) are infeasible in acoustic communication due to significant channel distortions. As a result, OFDM-based systems achieve similar throughputs as those based on FSK. Both FSK and OFDM are only suitable for short-range communication between stationary devices [84].

c) **CSS**: With the ability to handle dynamic channel conditions and extend communication ranges, CSS is arguably the most dominant modulation technique for acoustic communications [62], [60], [21], [61]. It employs noise-resilient chirp signals as carriers, making it robust to co-channel interference, path losses, multipath fading, and the Doppler effects [62]. A CSS frame starts with a preamble followed by different symbols as illustrated in Fig. 6. Both preambles and data symbols in a CSS frame use chirp signals but with different chirp rates. Though with significantly improved robustness, CSS still suffers from low transmission rates.

3) **Challenges for Waveform Design**: Next we discuss two design challenges in devising or selecting suitable waveforms for acoustic sensing and communication.

- Though transmissions in the range from 20Hz to 18KHz enjoy better channel gains and a relatively large bandwidth, their audibility limits the application scenarios. In contrast, transmissions in the inaudible range though in absence of unintended noise, suffer from a limited bandwidth and significant attenuation. Therefore, in choosing a suitable bandwidth for target applications, one needs to consider.

**Challenge V: Trade-offs among channel quality, bandwidth and audibility.**

- As discussed in TABLE II, existing waveforms either suffer from short communication ranges or low data rates.

**Challenge VI: Designing modulation schemes that are suitable for both high-speed and long-range inaudible aerial communication.**

To do so, one needs to devise robust high-order modulation techniques. One such approach is presented in Section IV-A3.

B. **Temporal Feature Extraction**

Temporal features refer to timing information such as onsets, time-of-arrival and time-difference-of-arrival. This section focuses on the techniques to extract these features.

1) **Onset Detection**: Onset detection, determining the presence and the start time of a particular reference signal is the cornerstone of acoustic communication and time-sensitive sensing applications.

Onset detection is often achieved via cross-correlation between the captured signal and a known reference signal. The waveform of the reference signal is carefully designed so that there exists a sharp peak in the correlation results when the reference signal is present; otherwise, the maximum correlation value is far below a pre-defined threshold (Fig. 7). As a result, in absence of multipath effects or strong interference, a simple threshold-based approach is sufficient to detect the presence of the reference signal and the timestamp of the maximum peak is recorded as the onset of the signal.

In practice, the accuracy of threshold-based onset detection is degraded by three phenomena, namely, device heterogeneity, the “near-far” effect and the multipath effects. Device heterogeneity refers to the fact speakers and microphones on 2

In communication system, the reference signal is often the preamble and hence onset detection is the same as preamble detection.

![Fig. 6: An example CSS frame](image1)

![Fig. 7: Illustration of signal onset detection.](image2)

![Fig. 8: (a) The correlation peak of distant samples is even weaker than the noisy peaks from closer ones, making it challenging to set an appropriate threshold for reliable onset detection. (b) Interference including clap noise and multipath effect can lead to incorrect timestamp estimation.](image3)
different devices have different gains. A constant threshold may not work for all devices. The “near-far” effect, a term originated from wireless communication systems, describes the phenomenon where the signal power received at a base station is dominated by the signals from closer user devices due to signal attenuation over distance. Similarly, in acoustic systems, when a transmitter and a receiver are close, the resulting correlation peak at the receiver can readily exceed a pre-defined threshold and hence the reference signal is detected (Figure 8(a)(a)). However, when their distance becomes larger, the respective correlation peak may fall below the threshold and in fact sometimes below the values caused by close-by interfering sources. In a multipath rich environment, a receiver not only captures the Line-of-Sight (LoS) signal but also receives multiple delayed and attenuated copies. These delayed and attenuated copies, called None-Line-of-Sight (NLoS) signals, can add up constructively and thus surpass LoS signals in peak intensity. A naive thresholding approach or simply finding the largest peak will result in false onset detection.

Fig. 8(a)(b) illustrates the effects of the three phenomena when the reference signal is a chirp signal. In the experiment, hand claps prior to the transmission of the chirp signal result in noticeable peaks even after cross-correlation at the receiver. Peaks due to NLOS paths are in fact larger than that from the LOS path.

2) Timing Estimation: Estimating Time-of-Arrival (ToA) or Time-Difference-of-Arrival (TDoA) of transmitted acoustic waves at target receivers builds upon onset detection and plays an important role in ranging and localization. Depending on whether the intended targets are equipped with acoustic transceivers, existing techniques can be further categorized into device-based and device-free approaches. Among device-based approaches, one-way or two-way sensing methods typically utilize cross-correlation to achieve sample-level timing resolutions. In device-free approaches, to estimate the time-of-flight between transmission and the reception of reflected waves from a target, phase information can also be used to achieve subsample-level resolutions.

a) One-Way Sensing: One-way sensing generally refers to a sensing paradigm where time information is obtained through unidirectional transmissions. In this paradigm, the transmitter or receiver can be multiple separated devices or a single device with multiple channels as shown in Fig. 9. One-way sensing is achieved via tight synchronization so that a receiver knows precisely the onset of an acoustic transmission to estimate its flight time. For time synchronization, this approach often exploits another high-speed signal sources [115], [70]. These signal sources are often radio signals such as WiFi, Bluetooth, and Zigbee whose propagation time is negligible within the maximum range of acoustic waves. For ToA estimation, an acoustic signal and a synchronization signal are transmitted simultaneously. A receiver determines the ToA from the difference in arrival time between the two signal sources.

For TDoA estimation, multiple transmitters or receivers need to be tightly synchronized. In some cases, transmitters or receivers co-locate physically on a single device as shown in Fig. 9(b). In transmitter-synchronized systems [61], [60], acoustic transmissions are triggered concurrently and they arrive at a receiver after different propagation delays. TDoA is then obtained by cross-correlating received samples with known reference signals. In receiver-synchronized systems, TDoA is computed by cross-correlating the received samples from different receive channels [69] as shown in Fig. 9(b). One-way sensing is simple and effective in extracting time information. However, the main drawback lies in its needs for tight synchronization, especially for cases where distributed devices are involved. This tight synchronization requirement can be compromised by Challenge III (i.e., uncertain system delays), thereby significantly affecting the timing performance. Though the uncertainty can be mitigated by either kernel-level implementation on general-purpose OSs or customized hardware, the applicability of one-way sensing is severely restricted.

b) Two-Way Sensing: To relax the need for tight synchronization, two-way sensing has been proposed at the expense of increased hardware and processing complexity. In two-way sensing, acoustic transmissions are bi-directional. It is assumed that each device is equipped with both a speaker and a microphone. Extracting ToA information between two devices is shown in Fig. 10(a). At time $t_A$, device A starts an acoustic transmission. Device B detects the acoustic signal at time $t_B^r$ and starts another transmission at time $t_B^s$ after an arbitrary delay. Device A detects the second transmission at time $t_A^r$. Therefe time information (ToA) can be derived as [92]:

$$t = \frac{1}{2} (t_A^r - t_A^s) - \frac{1}{2} (t_B^r - t_B^s).$$  \hspace{1cm} (5)

If both transmissions can be received by a third device, then time differential information (TDoA depicted in Fig. 10(b))
can be derived by [123]:

\[ t = \frac{1}{2} (t_A' - t_A^*) + \frac{1}{2} (t_B' - t_B^*) - (t_C' - t_C^*). \]  

(6)

Note that in presence of uncertain system delay (Challenge III), \( t_A', t_A^*, t_B', t_B^*, t_C', t_C^* \) cannot be recorded precisely in user applications. To overcome such a challenge, two novel techniques have been proposed in [92]. First, in addition to transmissions from other devices, each transmitting device also records its own transmission through its on-board microphone. Second, sample counting in the audio buffer of a device is used to estimate the time elapsed between consecutive acoustic receptions. Combining with the known distance (and thus known propagation delay) between the microphone and the speaker on each device, one can then estimate TOA and TDOA following Eqn. (5) and (6).

3) Phase-enabled Fine-grained Timing: Both one-way and two-way sensing for TOA or TDOA rely on cross-correlation to determine the onset of signals, whose resolution is limited by the sampling rate of respective devices. At a sampling rate of \( f_s = 48 \text{kHz} \), the time resolution is upper bounded by \( \frac{1}{f_s} \approx 2.1 \times 10^{-5} \text{s} \), or equivalently a range resolution of 7 mm if the sound speed is 340 m/s. However, CC-based onset detection often suffers from 2 to 3 samples errors [87], resulting a timing error from 40 to 60 \( \mu \text{s} \). To achieve finer time granularity, other signal features should be exploited. In device-free sensing, since the acoustic transmitter and receiver are co-located, to estimate the time flight of reflected waves from interested targets, phase information can be exploited. The relationship between phase changes and time is waveform-dependent. We next present the basic approaches to extract phase from three waveforms discussed in Section III-A1, namely, pure tone signals, FHSS signals, and chirp signals.

a) Pure Tone Signals: The phase of pure tone signals can be extracted by a coherent receiver whose structure is shown in Fig. 11. In a coherent receiver, two identical copies of an input signal are multiplied by \( \cos(2\pi f t) \) and its \( \frac{\pi}{2} \) phase shifted version \( -\sin(2\pi f t) \), respectively. After a low pass filter, the In-phase (I) and Quadrature-phase (Q) components can be obtained. The absolute phase \( \theta \) in \( s(t) = \cos(2\pi f t + \phi) \) is calculated by \( \tan^{-1}(Q/I) \). Phase changes can be determined by subtracting consecutive absolute phase as illustrated in Fig. 12(a). Consider a pure tone oscillating at \( f_c = 20 \text{kHz} \) and the sampling rate is \( f_s = 48 \text{kHz} \). One sample interval corresponds to a phase change of \( \frac{\pi f_c}{f_s} \approx 2\pi = \frac{\pi}{2}\pi \). Therefore, if the detectable phase change is below \( \frac{\pi}{2}\pi \), one can readily achieve sub-sample time resolution. Since such a \( \frac{\pi}{2}\pi \) phase change is comparable to the maximum \( 2\pi \) value, phase-based approaches generally outperform CC-based ones in time granularity. A major shortcoming of pure tone signals is their vulnerability to background noise and multipath effects.

b) FHSS Signals: The demodulated baseband signal \( y(n) \) from receiver together with the original known one \( x(n) \) are then utilized to estimate the Channel State Information (CSI, or Channel Impulse Response, hereafter, we will use CSI instead) \( h(n) = \frac{x(n)}{y(n)} \) in (complex form), where \( n \) represents the sample index. We are often particularly interested in a specific index \( n_s \) of \( h(n) \) as they may reflect interactive actions such as finger movements or respiration. The absolute phase of \( h(n_s) \) is not useful but if we track its phase difference in consecutive frames as illustrated in Fig. 12(a), we can be able to track the phase of, say finger-generated echo hence locate it. This can also handle ambient static noises as they are excluded by subtraction. The aforementioned processing steps including CSI estimation first and then CSI phase differentiation has become the routine for FHSS signal based applications. FHSS signal is sensitive enough to detect small phase changes but subjects to various channel distortions such as path loss and the Doppler effect hence is only suitable for around device sensing. To sense at long range or low SNR, chirp signals are more appropriate.

c) Chirp Signals: Extracting phases from chirp signals is achieved through chirp mixing, which converts time information into frequency features as illustrated in Fig. 12(b). Assume that the received signal \( s'(t) \) is a delayed and attenuated version of a transmitted signal \( s(t) = \cos(2\pi f_{min}(t - \Delta t) + \Delta \phi(t - \Delta t)^2) \). In other word, \( s'(t) = As(t - \Delta t) = A \cos[2\pi \left(f_{min}(t - \Delta t) + \frac{\Delta \phi}{2\pi}(t - \Delta t)^2\right)] \). In chirp mixing, we multiply \( s(t) \) and \( s'(t) \) and feed the resulting signal through a low pass filter. The mixed results become \( s_{mix}(t) = A \cos[2\pi \Delta t \frac{\Delta \phi}{2\pi} t + 2\pi f_{min}(t - \pi \Delta t^2)] \). Clearly, \( s_{mix}(t) \) is a single tone signal with frequency \( \frac{\Delta \phi}{2\pi} \). Applying a Discrete
Fourier Transform (DFT) on $s_{\text{mix}}(t)$, we can estimate $\Delta t$ by $f_p \cdot T/B$, where $f_p$ is the peak frequency after DFT. From the discussion, we see that the timing resolution of chirp mixing is upper bounded by its frequency resolution multiplied by a constant. The frequency resolution of DFT is proportional to $\frac{1}{T}$. Therefore, the granularity of $\Delta t$ is proportional to $\frac{1}{T^2}$. For example, for a chirp signal in the range of 18KHz to 24KHz, we have a timing resolution of 0.167ms. To further improve the timing resolution, phase information in the mixed signal can be utilized. We see that in the frequency bin $f_p = \Delta f \frac{T}{2}$, the phase of the mixed signal $\phi(t) = 2\pi \left( f_{\text{min}} \Delta t - \frac{1}{2} \frac{f_p}{T} \Delta t^2 \right)$. Therefore, a time difference of 10$\mu$s corresponds to a phase difference of 0.18 radian when $f_{\text{min}} = 18$KHz, notable enough to be detected. The phase differences can be estimated over multiple chirps.

Theoretically, phase-based methods can be combined with one-way sensing since the transmitter and receiver devices are synchronized. However, carrier frequency offsets due to clock drifts, introduce constant phase shifts and result in large time errors in the long run.

4) Challenges for Temporal Feature Extraction:

- As discussed in Section III-B1, the near-far effect and device heterogeneity problem make the use of constant threshold in onset detection inadequate. Multipath effects and strong interference also pose challenges in onset detection.

**Challenge VII:** Robust onset detection under dynamic channel conditions.

A possible solution is to set thresholds dynamically based on the perceived noise level. More discussions can be found in Section IV-B3.

- Design considerations such as waveforms, duration and bandwidth of signals will affect the accuracy and resolution of timing estimation in different approaches. In general, longer time interval and larger bandwidth lead to higher timing accuracy. Transmitting multiple frames is also instrumental phase estimation. However, there is a trade-off between the timeliness of the estimation (e.g., in highly dynamic scenarios) and performance.

**Challenge VIII:** Identifying suitable configurations to achieve a good trade-off between performance and adaptiveness to dynamic changes in timing estimation.

C. Channel Profiling

This section presents channel characterization techniques for application development. The objective of channel profiling is to find specific acoustic features and their precise relationships with respective states. These acoustic features, formally defined as channel characteristics or Channel State Information (CSI), here includes influences from both acoustic front-ends and acoustic medium that shape these acoustic features. The construction of a precise relationship is also called channel modeling. In can be in the format of explicit mathematical model or implicit mapping, derived from model-driven and data-driven approaches, respectively. A canonical data flow of common channel modeling methods are shown in Fig. 13. We now first start with CSI representation.

1) CSI Representation: As we mentioned before, CSI representation is to find a specific acoustic feature, say Doppler frequency, to decipher respective states, say hand gestures. To find a successful CSI representation is non-trivial and often requires sophisticated domain knowledge and intensive observations. The first thing in CSI representation would be acquiring adequate preliminary information on common acoustic features and acoustic channel characteristics, which can be found in Section II-A. Having profound knowledge on acoustic basics would be helpful to strike best features to reflect respective states. In this section, we present typical CSI representations for acoustic characteristics outlined in Section II-B.

Path Loss, Reflection, Refraction, and Diffraction: These generic wireless properties of acoustic signals can be a double-edge sword for acoustic sensing. They can on one hand attenuate signal strength and result in multipath effect hence affect signal quality and therefore are harmful; on the other hand, they can reflect spatial information and therefore is useful for applications such as localization. A common adoption to reflect these properties is using correlation spectra. To avoid the side effects by these properties, one can use sophisticated waveform design outlined in Section III-A to obtain correlation spectra that can disentangle multiple reflections. Often, waveforms such as chirp signals that have high correlation and processing gain is favorable as multiple reflections are separable if using these signals. For passive sensing system, the features in the correlation spectra may not be noticeable hence require dedicated signal processing. Since these signal processing tricks are application-dependent, we postpone any further discussions on the application layer. To harness the multipath effect, one should adopt waveforms that can enrich acoustic profiles. This could be achieved by wide-band sensing using signals of a relatively long duration. However, using signals of long duration would increase latency hence trade-off between latency and duration should be made.

Doppler Effect: To estimate the Doppler effect of a target, one often lets a device to transmit a pure tone signal due to its high Doppler accuracy as we mentioned in Section III-A1. If the target owns an acoustic-enabled device, we then use this device to capture transmitted signals and perform DFT analysis in a sliding window fashion. Through this, we obtain the major frequency of received signals over time. To this end, we follow Eqn. 2 to estimate the Doppler effect. Note that in practice, multiple tones may be transmitted and one can average the result from each tone so as to improve estimation accuracy. For targets without any devices, we can track the Doppler frequency by their acoustic reflections. The major difficulty here lies in the method to pin down target induced acoustic reflection in the presence of strong self-interference. The adoption of self-cancellation techniques and the utilization of prior information would be common practice. For instance, the walking speed of human beings typically being around 1 m/s can be used to confine the search range in DFT results to obtain a target’s moving speed.

Temperature Effect: As we mentioned earlier in Sec-
tion II-B, the propagation speed of acoustic signals is dependent on ambient temperature. Therefore, CSI representation in this case is rather straightforward. Since speed can be derived by the division between distance and time, and we have plentiful approaches for timing estimation discussed in Section III-B2, time is thus more suitable for CSI representation.

**Acoustic Dispersion:** Recalled that acoustic dispersion describe a phenomenon that different acoustic frequency components propagate at heterogeneous speeds in solid medium as revealed by Eqn. 4. This phenomenon could be observed by a rather distinctive time-domain waveform dictated in Fig. 4. This in turn indicates that time-domain acoustic waveform would be a possible choice for CSI representation. Application based on time domain acoustic dispersive waveform can be found in Section IV. Meanwhile, as different frequency components arrival at different time, when converting time-domain waveform into frequency spectrogram, we may observe particular waveform shaped by frequency versus time. If we could interpolate this waveform by, say linear interpolation, we can thus utilize the curvature of the waveform for CSI representation. This curvature may reveal distance [53] or material information. When the curvature is not obvious or the waveform cannot be readily interpolated, magnitude spectrogram or other common acoustic features such as MFCC or GFCC may be alternative choices. Note that acoustic dispersion phenomenon is observable only when there are multiple frequency components so that in active sensing, signals of wide bandwidth like chirp signal is preferable. In passive sensing, acoustic signals produced by natural events generally contain a rich set of multiple frequency components.

**Acoustic Resonance:** In acoustic resonance enabled applications, the goal is to inspect resonance properties of a particular object. Therefore, the primary setting is to place sensors including (piezo) microphone and (piezo) speakers tightly on this object and focus on the properties of structure-borne acoustics. We then actively transmit wide-band signals such as chirp signals through this piezo speaker and let the piezo microphone to capture the transmitted signals. Following that, DFT is typically applied to check the frequency response of received signals. In order to detect minor resonance frequency change, it is desirable to utilize a high sampling rate so that DFT results can achieve better frequency resolution. From the aforementioned processing steps, we can infer possible CSI representations, for instance, peak frequency or frequency response. An appropriate CSI representation can often ease significant efforts on model construction. With appropriate CSI representations, the next step is to build an application-specific model.

2) **Channel Model Construction:** Constructing an appropriate channel model is the cornerstone for acoustic sensing application development. A canonical data flow of common channel modeling methods are shown in Fig. 13. The basic idea behind channel model construction is to map respective states, say hand moving directions, to certain CSI representations, say Doppler frequency. A naive approach, also called *Data-Driven* (DD), to construct this model is through direct mapping, which often involves massive data and intensive training. Another method, known as *Model-Driven* (MD), formulates this mapping with a close-formed expression, which are often more efficient but non-trivial to achieve. The respective advantages, disadvantages, and suitable applications for these two methods are displayed in TABLE III. In this section, we highlight the basic steps for aforementioned two common channel model construction methods.

Model-driven approach, formulating acoustic sensing problem as regression, can be effective and efficient, which however, require sophisticated signal processing designs and specific domain knowledge hence is often remarkable challenging. The key insight behind MD approaches is to mathematically quantify the relationship between CSI and certain application-specific states through regression, say mapping hand moving direction to specific Doppler frequency shift in a close-form equation. Actually, the hard part of this approach is to discovery the respective CSI and make it notable via signal processing techniques. Additionally, this approach may only be suitable when CSI is a scalar variable. Since these signal processing techniques are application-specific, we hence postpone their discussions in the next section.

Since a close-form or explicit parametric model is often hard to craft, one often resort to DD approach. The DD approach, taking acoustic sensing as categorical problem, implicitly builds the inference model by directly mapping CSIs with respective application-specific states. This approach is more suitable to handle the cases when CSI is in the format of a vector, say frequency response, or matrix, say MFCC.

| Problem | Advantages | Disadvantages | Suitable applications |
|---------|------------|---------------|----------------------|
| MD      | Regression problem | Effective and efficiency | Require domain knowledge, time-consuming | Temporal feature/channel characteristics |
| DD      | Categorical problem | Simple in model designs | Massive data, computation-intensive, heterogeneity problem | Channel characteristics |
TABLE IV: Categorizing acoustic sensing enabled applications.

| Category                        | Key physical layer                           | Core processing techniques                     | Applications                                                                 |
|---------------------------------|----------------------------------------------|------------------------------------------------|------------------------------------------------------------------------------|
| Aerial acoustic communication   | Acoustic hardware, acoustic channel property | Waveform design                                 | Communication [50, [62], [84], [120]                                        |
| Temporal feature based applications | Acoustic hardware, acoustic channel property | One-way sensing/Phase-enabled accurate timing   | Ranging [92], [115], [146]                                                  |
|                                 |                                              | Signal onset point detection, Phase-enabled accurate timing | Acoustic radar [148], [93], [75]                                             |
|                                 |                                              | Signal onset point detection, one-way/two-way sensing | Localization [60], [61], [70], [123], [113], [64], [21], [85], [68]          |
|                                 |                                              | Phase-enabled accurate timing                   | Device-based tracking [74], [77], [141], [117]                               |
|                                 |                                              |                                                 | Device-free gesture tracking [87], [122], [142]                              |
|                                 |                                              |                                                 | Biometric sensing [135], [109], [118], [45], [58], [59]                      |
|                                 |                                              |                                                 | Gesture recognition [43], [105], [65], [124], [32], [111]                    |
| Channel characteristics enabled applications | Acoustic hardware, acoustic channel property, platform diversity | Over-the-air channel profiling                  | Speaker authentication [24]                                                  |
|                                 |                                              |                                                 | Novel interactive control [57]                                                |
|                                 |                                              |                                                 | Keystroke detection [53]                                                     |
|                                 |                                              |                                                 | Force detection [114]                                                        |
|                                 |                                              |                                                 | Touch recognition [90]                                                       |

The basic idea behind DD approach is fingerprinting. This approach first collects sufficient data (CSIs) under respective states in an offline manner and then utilize these data to train a model using machine learning techniques. The model is then used online to predict the corresponding state with respect to its input data. Such a processing pipeline may require less sophisticated domain knowledge hence is comparatively easier than MD approaches. Nevertheless, this approach requires massive data or constant calibrations due to device heterogeneity problem hence is labor intensive. Meanwhile, high computational cost and storage requirement are other drawbacks for this method.

3) Challenges for Estimating Channel Characteristics:

- As having been outlined, mining the specific CSI to reflect particular application-specific state requires sophisticated signal processing techniques and domain knowledge hence is remarkable difficult. Therefore, the challenges is

  Challenge IX: Discovering appropriate CSI representation.

This may require strong background and intense observations. An optional choice is resorting to customized hardware that offers more flexible physical-layer configurability, so as to gain more opportunity to enhance the acoustic features, thereby facilitating CSI extraction. More discussions on this can be found in Section V.

- As we mentioned earlier, channel models, especially those using DD approaches, may be platform-dependent, so it requires constant calibrations or user configurations when deploying a particular acoustic sensing applications on heterogeneous platforms. As a result, it is particularly challenging in

  Challenge X: Building cross-platform acoustic sensing channel models.

Potential solutions to this problem may be few shot learning techniques [126] or domain adaptation methods [78] and more discussions on this can be found in Section IV-C3.

IV. ACOUSTIC SENSING APPLICATIONS

Now we turn to acoustic sensing applications driven by the mechanisms discussed in Section III. Existing applications fall into three categories according to their respective supporting mechanisms, namely aerial acoustic communication, applications leveraging temporal features, and solutions enabled by channel characterization. For each application, we review key enabling techniques and performance achieved. Potential future directions for each categories are also discussed. A taxonomy of acoustic sensing applications is given in Table IV.

A. Aerial Acoustic Communication

Exploiting aerial acoustic channels or air-borne acoustic signals for communication, known as aerial acoustic communication, has attracted much attention recently. Aerial acoustic communication enables any device that has embedded microphones and speakers to communicate without extra hardware or complex network configuration. It can serve as an alternative to traditional RF-based device-to-device communication such as Bluetooth, Near Field Communication (NFC), and WiFi Direct. In a nutshell, aerial acoustic communication is realized by representing information as a function of different waveform configurations. As summarized in TABLE V, different schemes mainly differ in the waveforms and bandwidth utilized, which result in different data rates, operational ranges and audibility.

1) Short-range Aerial Acoustic Communication: The authors in [37] presented a communication system by manipulating the properties of pure tone signals. It leverages the presence or absence of tone signals to represent information (100% Amplitude Shift Keying). This approach achieves a data rate of 5.6 kbps with multiple audible tones. The data rate reduces to 1.4 kbps when a single inaudible tone is used. A maximum communication range of 2 m can be achieved under LOS conditions. Another work called Digital voice [71] modulates data bits in the audible band (under 12 kHz) via Mary FSK, reporting a data rate at tens to thousands of bits per seconds (bps). Dhwani [84] is an acoustic-based NFC system. It employs OFDM modulations to encode messages
and incorporate a technique called JamSecure to prevent malicious attacking. Dhwani occupies a bandwidth of 24 kHz and achieves a maximum data rate of 2.4 kbps. The authors of [44] propose an acoustic-enabled mesh network built upon FHSS over 4.2 kHz to 21 kHz. The above work all utilize the audible band (normally below 18 kHz). Transmitting information over audible bands can be disruptive and thus several inaudible (hidden) communication systems are developed. The authors in [72] propose to leverage the masking effect of the human hearing system to achieve inaudible acoustic communication, saliently addressing Challenge-II. It employs OFDM modulation and achieves a data rate of 240 bps. Similar work in [140] and [120] attain data rates of 600 and 500 bps, respectively.

2) Long-range Low Data Rate Communication: Neither tone-based nor OFDM modulation techniques are robust to Doppler effects. The performance of these methods further deteriorates in multipath-rich environments, making them inadequate for long range communications. In contrast, chirp spread spectrum (CSS) utilizes more interference-resilient chirp signals to encode information bits and thus achieves lower bit error rates and longer communication ranges. A chirp binary orthogonal keying (BOK) modulation technique is first presented in [14], [33]. It utilizes orthogonal up and down chirp signals for modulation. The work in [62] adopts BOK and realizes a communication range up to 25 m at a data rate of 16 bps. Soonwon et al. [50] improve upon BOK and develop a chirp quaternary orthogonal keying (QOK) modulation technique. QOK finds near-orthogonal chirps by an exhaustive search over a pre-defined solution space. With QOK, a Code Division Multiple Access (CDMA) system is built. The system achieves zero frame error rate even at a minimal sound pressure level of 35 dB SPL when the transceivers are 2.7 m away from each other. The authors of [21] propose a pseudo-orthogonal CSS modulation where up- and down-chirps overlap in time and thus its transmission rate is doubled. CSS and its variants often achieve less bit error rates and long communication ranges compared with other modulation mechanism. However, the achievable data rate is less competitive as this method is inherently less bandwidth efficient.

3) Long-range High-speed Communication via Loose Orthogonal Modulation: To achieve long-range communication at relatively high data rates (addressing Challenge-VI), a loose orthogonal modulation approach is proposed in [20]. Its basic idea is to overlap multiple chirp carriers in a single time slot to boost throughput. Though inter-carrier-interference is introduced, its adverse effect can be mitigated, say, by rate adaptation. The reported maximum throughput is 1 kbps, over 60x of that of existing CSS-based approaches. Even at a distance of 20 m, a data rate of 125 bps can be reached.

4) Research Opportunities: Aerial acoustic communication is gaining attraction as an alternative for device discovery and communication. In fact, audio interfaces has become a part of Google’s nearby peer-to-peer communication APIs [9]. However, low data rates continue to hamper its wide adoption. For instance, in-vehicle networking demands at least 10 kbps data rate [143], far exceeding the maximum throughput attainable by existing aerial acoustic communication systems. Data rates of aerial acoustic communication can be further increased by incorporating more complex techniques such as rake receivers, multiple-input-multiple-output, and advanced coding mechanisms. Another opportunity arises from the exploitation of SS channels as discussed in Section II-B. Most existing works are restricted to AS for communication while SS is rarely considered with the only exceptions are [102] and [101]. In [102], the authors modulate the vibration motors available in mobile phones, and decoding information through accelerometers. A maximum of 200 bps data rate is achieved. In their follow-up work [101], the throughput is boosted to 30 kbps by replacing the receiver with a high-sensitivity microphone and the adoption of high-order OFDM modulations. We envision that more efficient modulation techniques for SS channels can be devised. Furthermore, combining AS and SS in a single system poses new challenges and exciting research venues in acoustic communication.

### B. Applications Leveraging Temporal Features

In this section, we present applications leveraging temporal features including acoustic ranging, localization, device-based tracking, device-free gesture tracking, and respiration sensing. For each application, we discuss state-of-the-art solution approaches and how some the challenges outlined in previous sections are addressed.

1) Ranging: Range (the relative distance between two devices) provides a useful contextual information and can be used for distance and size measurements, network management [83], and content sharing [35], [29]. Leveraging acoustic

| Work          | Modulation mechanism          | Maximum operating range (m) | Bandwidth (kHz) | Audible or inaudible | Bit rate (bps) |
|---------------|------------------------------|-----------------------------|-----------------|---------------------|----------------|
| [37]          | OFDM                         | < 2                         | 0.735 – 4.41, 18.4 | Audible or inaudible | 5600, 1400     |
| Digital voice [71] | M-ary FSK                  | < 2                         | 0 – 12          | Audible             | 2400           |
| [44]          | FHSS                         | 20                          | 4.1 – 21        | Audible             | 20             |
| Dhwani [84]   | OFDM                         | < 1                         | 0 – 24          | Audible             | 2400           |
| [72]          | OFDM                         | 8                           | 6.4 – 8         | Inaudible           | 240          |
| [140]         | Phase modulation via complex lapped transform | < 2 | 6.4 – 8 | Inaudible | 600 |
| Dolphin [120] | OFDM                         | 8                           | 8 – 20          | Inaudible           | 500            |
| [62]          | BOK                          | 25                          | 19.5 – 22       | Inaudible           | 16             |
| [50]          | QOK                          | 2.7 m at 35 dB SPL          | 18.5 – 19.5     | Inaudible           | 15             |

TABLE V: Comparison of aerial acoustic communication systems.
signals for ranging is an economical and convenient alternative to traditional measurement tools. Ranges are computed by multiplying time of flight derived from techniques in Section III-B with the propagation speed of acoustic signals, generally assumed to be constant and known a priori. Ranging errors are defined as the Root Mean Square (RMS) of the differences between estimated results and the ground truth, while ranging accuracy is inversely proportional to the RMS error. The ranging performance heavily relies on techniques at the processing layer, in particular, robust onset detection. A comparative study is shown in TABLE VI.

BeepBeep [92] is a pioneer work that uses acoustic signals for precise ranging on commodity mobile devices based on ToA via a two-way sensing method. It cleverly circumvents unknown system delays (Challenge-III) and clock synchronization by directly retrieving timestamps from acoustic samples themselves. To mitigate multi-path effects aroused from Challenge-IV, the authors locate the earliest “sharp” peak after cross-correlation. BeepBeep reports centimeter-level (2 to 6 cm) ranging errors. However, the performance of BeepBeep can be degraded by presence of strong NLOS paths. The authors in [115] sidestep uncertain and variable system delays in acoustic playback and recording hence addressing Challenge-III by a kernel space implementation, and build a standalone application called RFBeep. RFBeep [115] performs ranging with ToA using one-way sensing. It reports decimeter-level (up to 50 cm) ranging errors within 16 m. However, the reliance on kernel modification prohibits its wide-scale adoption. SwordFight [146] is another ranging solution that improves upon BeepBeep in responsiveness, accuracy, and robustness. It works at the same way as BeepBeep but differs in transmitted waveforms and onset detection strategies. It reports a median ranging accuracy of 2 cm with 12 Hz fresh rate in noisy environments.

2) Acoustic Radar: Similar to RF radars, acoustic radars work by radiating acoustic signals and estimating the round trip time of reflected echoes. It can be used in obstacle avoidance and mapping. Since acoustic echoes attenuate sharply with the increase of distance \( d \) (e.g., in free space, proportional to \( \frac{1}{d^2} \) [142]), the operational range of acoustic radars is often limited. Multipath effects also pose additional challenges as it is often difficult to disentangle desired echoes bouncing off targeted objects from those experiences multiple reflections or reflected off undesired objects (Challenge-VII). The evaluation metrics for acoustic radars are the same with the one used in ranging.

In [40], the authors proposed a sonar sensor for depth sensing on smart phones utilizing the phone’s microphone and rear speaker. The reported ranging errors up to 12 cm within 40 m distances. Further improvement to ranging accuracy using deep learning techniques is proposed in [75]. In this work, Synthesized data is used to train a neural network to handle platform diversity, multipath effects, and background interference, addressing Challenge-IV and Challenge-VII simultaneously. The resulting range error can be as low as 1 cm at a distance up to 4 m and is agnostic to various background noises, heterogeneous devices, etc. BatMapper [148] is among the first work that demonstrates the feasibility of commodity mobile devices to act as acoustic radars for indoor floor map construction. It exploits speaker-microphone distance constrains to construct a probabilistic model to extract echoes bouncing off surrounding objects, which allows it to mitigate multipath effects (Challenge-VII) for robust onset detection and thereby achieve accurate range estimation. BatMapper reports 1–2 cm estimation errors with ranges up to 4 m. With the assistance of on-board Inertial Measurement Unit (IMU) including a gyroscope and an accelerometer, its 80-percentile errors are less than 30 cm in geometric floor reconstruction. SAMS [93] is another acoustic radar solution that improves upon BatMapper. Different from the correlation method adopted in BatMapper, SAMS utilizes chirp mixing, a finer temporal feature extraction method, which can circumvent insufficient sampling rates for better temporal resolution. SAMS reports a median error of 30 cm and a 90-percentile error of 1 m.

Compared to ranging between acoustic devices, acoustic radars rely on weak reflected signals from target objects for ranging measurements. Therefore, it is much more challenging to design appropriate signal processing techniques and robust acoustic waveforms for acoustic radars. A technical comparison among different ranging approaches is given in TABLE VI.

3) Localization: Localization is a key enabler for Location Based Service (LBS). Despite tremendous research efforts on indoor localization, many existing solutions either require expensive dedicated infrastructures [133], [13], [144] or rely on cumbersome device-dependent kernel hacking [116], [56], [55], [26], prohibiting their practical deployment. Among existing cutting-edge indoor localization approaches, acoustic-based systems attract much interests since they can achieve sub-meter level localization accuracy with relatively low infrastructure costs and deployment efforts. The underlying techniques for these localization systems are the timing measurement methods discussed in Section III-B2 and the major challenge is Challenge-VII. The evaluation metric for localization systems is RMS error. In this section, we present existing

| Ranging solution | Key processing techniques | Waveform design | Occupied bandwidth (kHz) | Ranging error |
|------------------|---------------------------|-----------------|--------------------------|--------------|
| BeepBeep [92]    | Two-way sensing           | Chirp signal    | 2 – 6                    | An average around 1 to 2 cm within 10 m |
| RFBeep [115]     | One-way sensing           | Tone            | NA                       | Around 30 cm median error within 16 m |
| SwordFight [146] | Two-way sensing           | Tone            | 0 – 11.025 or 0 – 16    | A median of 2 cm within 2 m distance |
| BatMapper [148]  | Finer temporal feature    | Chirp signal    | 8 – 16 and 8 – 10       | Up to 2 cm within 4 m distance |
| SAMS [93]        | Finer temporal feature    | Chirp signal    | 11 – 21                  | A median of 30 cm and a 90-percentile of 100 cm within 5 m |
| DeepRange [75]   | Finer temporal feature    | Chirp signal    | 18 – 22                  | A median of 1 cm within 4 m |

TABLE VI: Comparison of different ranging techniques.
works on acoustic-enabled localization solutions in two categories, namely, \textit{infrastructure-based} and \textit{infrastructure-free}. A comparison of related work is summarized in TABLE VII.

\textbf{Infrastructure-based} schemes typically deploy low-cost and power-efficient distributed acoustic anchors in target areas. The locations of these anchors are determined in advance. Apart from acoustic transceivers, each anchor may be equipped with wireless modules to communicate among themselves or with a remote server. The remote server can coordinate the transmission schedule among the anchors either in synchronous or asynchronous manner. When the transmitted acoustic signals are detected by either a target or other anchors, the associated timestamps (ToA or TDoA) are obtained. Finally, the location of a target is determined using trialateralization or more sophisticated optimization methods. In the subsequent discussion, we first review synchronous schemes, and then asynchronous approaches.

In [70], Liu et al. developed a centimeter-level localization system named Guoguo. The anchors in this system are synchronized by Zigbee and are scheduled to transmit orthogonal codes, which are used by targets to perform ToA estimation via one-way sensing. Multilateralization is then used to locate the targets. A speaker-only localization system was proposed by Lazik and Rowe in [61]. In their approach, distributed speakers are connected to different synchronized channels of an advanced audio device that transmits chirp signals for localization. A target locates itself locally by performing one-way TDoA estimation. According to [61], its 95-percentile localization accuracy is within 10 cm. ALPS [60] improves upon the work [61] in deployment efforts. In ALPS, anchors are synchronized via Bluetooth, and each anchor is equipped with one microphone and one speaker. The locations of the anchors are efficiently obtained through acoustic-assisted simultaneously localization and mapping. ALPS reports average errors of 30 cm and 16.1 cm in locating targets and anchors. Recently, a ultrasonic localization system called UPS+ is presented in [64]. UPS+ leverages the non-linearity of receiver microphones (details are presented in Section IV-C3) to enable ultrasonic beacons to locate smart devices without ultrasonic sensors. Consequently, the audibility problem, induced either by \textit{Challenge-II} or \textit{Challenge-VIII}, is eliminated. UPS+ achieves centimeter-level accuracy in localization.

The localization accuracy of the aforementioned work is highly dependent on clock synchronization accuracy, which depends on network latency, non-negligible in a large-scale network. In contrast, asynchronous approaches can overcome such shortcomings. ARABIS [123] is an asynchronous acoustic localization system that utilizes two-way ranging [92] to avoid the need for synchronization. In ARABIS, anchors transmit acoustic beacons periodically following a coarse time-division-multiple-access schedule. Targets, as well as anchors, overhear the transmissions and record the corresponding timestamps. These timestamps can be used to estimate TDoA information in locating a target. ARABIS reports a 95-percentile localization error of 7.4 cm. AALTS [21] improves upon ARABIS by a more robust onset detection approach to handle the near-far problem, hardware heterogeneity, and multipath effects. To handle these challenges (from \textit{Challenge-VII}, it normalizes the current correlation value by the mean of a number of its preceding samples. Additionally, a pseudo orthogonal chirp spread spectrum modulation technique is proposed, which effectively doubles the transmission rate. AALTS achieves 90-percentile tracking errors of 0.49 m for mobile targets and a median of 0.12 m for stationary ones with only four anchor nodes.

\textbf{Infrastructure-free} localization systems do not require the deployment of custom-built infrastructure devices in target areas. However, they tend to achieve less competitive localization accuracy compared with infrastructure-based solutions.

In [68], Liu et al. built a localization system utilizing acoustic and WiFi signals. It first estimates pair-wise distances within a device group via acoustic ranging [92], forming a spatial constraints. Each device in the group also uses WiFi fingerprints to impose another location constraints. By combining the two, target locations can be determined. This scheme achieves an 80-percentile localization error of 1 m. Since the computation of spatial constraints requires multiple pair-wise acoustic ranging measurements and is time consuming, the application of such an approach is limited to static target localization. Centaur [85], similar to [68], is a joint optimization framework utilizing acoustic and WiFi signals, and reports meter-level localization accuracy. The authors propose a novel multipath mitigation algorithm to address \textit{Challenge-VII}, and achieve robust onset detection. The key idea is to inspect signal changes in cross-correlation as opposed to absolute magnitudes considered in existing methods. EchoTag [113] is an acoustic fingerprinting localization system that can detect minor location changes. It associates different acoustic profiles

TABLE VII: Comparison of acoustic-enabled localization systems.

| Category          | Work          | Waveform design               | Additional signal | Key processing technique | Synchronous or asynchronous | Concurrent localization | Localization error |
|-------------------|---------------|-------------------------------|-------------------|--------------------------|-----------------------------|--------------------------|-------------------|
| Infrastructure-based | Guoguo [70]  | Chirp, duet pulse             | NA                | ToA (one-way)            | Synchronous                 | Supported                | Centimeter-level   |
|                   | [61]          | Chirp                         | NA                | TDoA (one-way)           | Synchronous                 | Supported                | Centimeter-level   |
|                   | ALPS [60]     | Chirp                         | NA                | TDoA (one-way)           | Synchronous                 | Supported                | Decimeter-level    |
|                   | UPS+ [64]     | Ultrasonic chirp, tone        | NA                | ToA (one-way)            | Synchronous                 | Supported                | Centimeter-level   |
|                   | ARABIS [123]  | Chirp                         | NA                | TDoA (two-way)           | Asynchronous                 | Supported                | Centimeter-level   |
|                   | AALTS [21]    | Chirp, pure tone              | NA                | TDoA (two-way)           | Asynchronous                 | Supported                | Decimeter-level    |
| Infrastructure-free | [68]          | Chirp                         | NA                | WiFi (two-way)           | Asynchronous                 | Not supported            | Meter-level        |
|                   | Centaur [85]  | Chirp                         | NA                | WiFi (two-way)           | Asynchronous                 | Supported                | Meter-level        |
|                   | EchoTag [113] | Chirp                         | Data-driven       | NA                       | Not supported                | Centimeter-level         |                  |
with different positions, known as tags, to train a classification model. This model is then used for online tag detection, enabling context-aware applications. EchoTag reports an accuracy of 98% in distinguishing 11 tags at 1 cm resolution. However, EchoTag is sensitive to environmental dynamics and will suffer from degraded performance in absence of new data collections. As a matter of fact, applications that are based on a fingerprinting strategy are subject to problems aroused from Challenge-IV and Challenge-X, limiting their practical adoption.

Although infrastructure-free solutions incur less hardware costs, they require labor-intensive site survey to obtain location-dependent signal profiles, making them sensitive to environment changes. Infrastructure-based approaches deliver a satisfactory localization accuracy at the cost of extra hardware. But the complexity in deploying multiple acoustic anchors and the synchronization requirements are still not economical and lightweight enough for practical deployment. To this end, the authors of [19] propose a single beacon-enabled passive localization system that can also identify a target. They discover that a footstep contains separable structure-borne and air-borne components. The former contains range information and the latter provides angle-of-arrival (AoA) along with identity signatures. Consequently, by placing a single acoustic array in the place of interest, a target can be simultaneously tracked and identified. Additionally, the domain adversarial training technique is employed in this proposal so as to enhance the generalizability of the system, easing the efforts in calibration and thus addressing Challenge-X. The reported median localization accuracy can reach 30 cm, which is highly enough given that a foot has a similar size. Another single acoustic anchors based proposal that leverage the geometry constraints shaped by LoS and NLoS acoustics can be found in [108] that reports 0.44 m localization accuracy across different environments. It is worth to mention that the aforementioned microphone array enabled localization techniques can obtain specific coordinates of a target rather than conventional source localization that can only obtain AoA information.

Compared to localization solutions utilizing RF signals [49], visible light [128], or IMU data [12], acoustic-enabled localization techniques strike good trade-offs between costs and accuracy. The acoustic diffraction property makes it feasible to locate targets in presence of small-scale random blockages. This puts less restriction on deployment. However, due to limited transmission ranges, more anchor nodes are needed in infrastructure-based localization systems.

4) Tracking: High-accuracy object tracking is important in many applications such as automated surveillance, traffic monitoring, and Augmented/Mixed Reality [139]. Tracking is a well-investigated topic in computer vision (CV) [139], [82], [132]. However, CV techniques impose substantial computation costs and do not work well under poor light conditions. Acoustic tracking systems can overcome these limitations. Depending on whether the targeted object can emit acoustic signals or not, existing solutions can be divided into device-based tracking and device-free tracking.

Device-based acoustic tracking aims to track acoustic emitting devices in motion. AAMouse [141] utilizes multiple carriers to estimate the Doppler speed of a target and integrates the speed over time for tracking. Though the reported tracking performance is at centimeter-level, tracking errors can accumulate over time, making it unsuitable for long-term tracking. CAT [74] improves upon AAMouse by adopting chirp mixing and boosts the tracking accuracy to a sub-centimeter level. However, due to the use of one-way sensing, it is sensitive to irregular SFOs [54], [80], [81] that cannot be easily compensated. Under the assumption of linear drift, CAT performs re-calibration when integration errors become intolerable hence allow the system to work sufficiently long. Another application of chirp mixing for high-accuracy tracking is presented in [77] where a drone follows a person with a safe range in challenging indoor environments. In this work, the authors introduce several advanced signal processing modules, in particular, MUltiple SIgnal Classification algorithm (MUSIC) to resolve multipath effects (aroused from Challenge-VII) and enhance system robustness. Furthermore, a reciprocal filter is introduced to address Challenge-I, compensating the frequency selectivity problem and thereby further enhancing the system stability. In Backdoor [103], a more precise compensation technique for frequency selectivity is proposed. First adopted in wireless communication, it equalizes channel effects by measuring channel state information using probe signals. Backdoor transmits acoustic signal in 40 kHz and takes advantages of non-linear diaphragm of power-amplifier so that sounds in the range of 20 kHz can be recorded. Thus, it does not suffer from the audibility problem (Challenge-II or Challenge-V). However, this approach requires customized hardware devices, making its adoption more difficult. LiLiSonic [117] achieves sub-millimeter 1D tracking accuracy in the presence of multipath using a single beacon with a small 4-microphone array. The high precision is achieved by

| System          | Waveform Design | Occupied bandwidth (kHz) | Tracking latency (ms) | Operation range (m) | Performance                  |
|-----------------|-----------------|--------------------------|-----------------------|---------------------|------------------------------|
| FingerIO [87]   | OFDM modulated  | 18 – 20                  | 5.92                  | < 0.5               | 8 mm (2D) average tracking error |
| LLAP [122]      | Multiple pure tones | 17 – 23                   | ≤ 15                  | 0.5                 | 5.5 mm (1D) and 4.37 mm (2D) average tracking error |
| Strata [142]    | GSM sequence    | 18 – 22                  | 12.5                  | 0.5                 | 3 mm tracking error          |
| [6]             | Chirp signal    | 18 – 20                  | 40                    | 4.5                 | 1.2 to 3.7 cm within 4.5 m   |
| CovertBand [88] | OFDM            | 18 – 20                  | 4.2                   | 6                   | A median of 18 cm tracking error |

TABLE VIII: Comparison of device-free gesture tracking systems.
leverage phase information after chirp mixing.

Device-free acoustic tracking tracks moving objects in an environment by reflected acoustic signals. Due to significant attenuation of reflected signals, high precision device-free acoustic tracking is often limited to short ranges. Next, we use finger, body posture tracking and respiration sensing as driving applications to discuss techniques in this category.

FingerIO turns a mobile phone or a smartwatch into an active sonar that is capable of tracking moving fingers for Around Device Interaction (ADI). Such a technology can extend the physical interaction boundaries hence is particularly useful for small wearables. FingerIO achieves a median accuracy of 8 mm [87] in 5.92 ms. It utilizes OFDM modulated signals to estimate the CSI between a hand and a smartphone periodically. In each estimation cycle, the CSI is acquired through cross-correlation. Since only moving fingers can dynamically affect the channel between the speaker and microphone, their movements can be tracked by comparing consecutive channel frames. Static multipath reverberations remain the same across frames and can thus be removed. The proposed technique successfully addresses Challenge-VII by extracting finger-movement-only CSI profiles, and inspired several follow-up work.

A multi-tone device-free gesture tracking system, LLAP, was proposed in [122]. It leverages coherent detection to extract the phases of acoustic echoes for finger localization and tracking. In LLAP, a mobile device actively transmits multiple tone carriers and decomposes finger-generated echoes via Empirical Mode Decomposition (EMD) for later processing. It further uses the phase divergence of multiple carriers to coarsely locate the start position of a finger and track its displacement via phase shifts. LLAP reports a tracking accuracy of 3.5 mm for 1D hand movement and 4.57 mm for 2D drawing with less than 15 ms latency. However, both FingerIO and LLAP are sensitive to nearby interference. To address nearby interference, another work named Strata was proposed in [142]. It also uses a coherent detector but applies a GSM training sequence modulated by Binary Phase Shift Keying (BPSK). Evaluation results demonstrate that it outperforms FingerIO and LLAP in all cases with an average tracking accuracy at 3 mm.

The aforementioned work considers micro-finger gesture tracking. For macro-body parts such as hand or the whole body, one often utilizes more powerful speakers to increase SNR so that the sensing range is larger. We hereby present tracking technologies on macro-body posture. The work in [76] shows that it is feasible to achieve room-level hand motion tracking with a customized platform. It employs an acoustic radar along with many advanced processing techniques including MIMO beamforming and deep learning for signal quality enhancement. The proposed system achieves 1.2-3.7 cm tracking errors within 4.5 m range and supports multi-user tracking. CovertBand [88] is an active sensing system for passive multiple object tracking. It builds on an active sonar with an enhanced speaker and uses the same parametric models as FingerIO [87] to track human body posture. CovertBand reports a median of 18 cm in tracking mobile targets. For static objects, it can achieve an accuracy of 8 cm with a distance up to 8 m in LOS conditions. A comparison of these tracking schemes is given in TABLE VIII.

The last category of applications concern continuous monitoring of human’s respiration rates and breathing patterns. With device-free acoustic tracking, one can estimate chest displacements caused by respiration over time of target subjects. A comparison of these techniques is shown in TABLE IX.

In [86], a portable life sign detection system based on commodity smartphones was presented. It uses a smartphone as an active sonar to detect chest movements for breathing rate estimation and sleep apnea detection. The proposed system can achieve an error of fewer than 0.11 breaths per minute (bpm) even at a distance of up to 1 m. Though the work of [86] utilizes an inaudible frequency range (above 18 kHz), it can still be perceived by animals and infants whose hearing systems are more sensitive to high frequency sounds. To deal with this audibility issue (Challenge-II) and handle Challenge-VIII, BreathJunior improves upon [86] by using white noise for respiration estimation [118]. Before transmitting chirp signals for sensing, it randomizes signal phases in frequency domain and recovers it at a receiver end making the generated sounds less obtrusive. The reported respiration rate error can be as low as 0.4 bpm at a distance of 40 cm. The work in [45] overcomes audibility issue (Challenge-II) by using Zadoff-Chu (ZC) sequence. As we outlined in Section III-A1, the FHSS modulated signal enables fine-grained multipath decomposition and allows multi-person respiration monitoring simultaneously. The reported error is within 0.6 bpm under various test environments in presence of multiple targets at a minimal distance of 10 cm. Ren et al. [98] developed a passive

| Work               | Waveform design | Bandwidth | Key techniques                                           | Performance                  |
|--------------------|-----------------|-----------|---------------------------------------------------------|------------------------------|
| BreathJunior [118] | FMCW & white noise | 24 kHz   | Phase-based accurate timing, beamforming                | 0.4 bpm at 40 cm, 3 bpm at 60 cm |
| RespTracker [45]   | ZC              | 2 kHz     | Phase-based accurate timing                              | Less than 1 bpm at 3 m, 0.8 bpm for moving targets |
| [98]               | NA              | NA        | Envelope detection                                       | Less than 0.05 bpm (device close to user) |
| BreathListener [135]| tone at 20kHz | NA        | Energy spectrum density, ensemble empirical mode decomposition, generative adversarial network | 0.11 bpm in driving environment |
| SpiroSonic [109]   | Multiple tones  | 17 – 24 kHz | Phase-based accurate timing, neural network regression   | 5%-10% error in lung function monitoring |

TABLE IX: Comparison between different biometric sensing systems.
sensing system that can detect breathing rates and sleep-related events from breathing signals. This approach employs high-quality sensors, and reports less than 0.5 bpm detection error rates.

The performance of previous solutions degrades significantly in noisy environments. To combat noise, BreathListener [135] extracts breath patterns from energy spectrum density and regenerates clean breath signal via a generative adversarial network. It achieves an average error of 0.11 bpm for breathing rate estimation in driving conditions. SpiroSonic [109] went one step further toward conducting spirometry tests in a regular home setting under various environment noises. It measures a target’s chest wall motion via acoustic radar and maps the obtained waveforms to lung function indices. SpiroSonic achieves 5% to 10% monitoring error in clinical studies, allowing reliable out of clinic disease tracking and evaluation.

5) Research Opportunities: We envision that research opportunities utilizing temporal features for acoustic sensing lie in two aspects. First, for large-scale deployments, existing approaches need to be made more robust to multipath effects, background noise, interference from ambient sound emitting sources (aroused from Challenge VII and the heterogeneity of consumer devices (Challenge-IV and Challenge-X). Infrastructure-based methods not only need to minimize initial setup costs, but also need to reduce operating costs, such as (repeated) site surveys and maintenance. Furthermore, solutions that are adaptive to environment changes or hardware upgrades or replacements are attractive. Second, novel applications utilizing accurate timing estimation on acoustic devices can be investigated. One such an example is AcuTe [16], where the authors leveraged the relationship between sound speeds and ambient temperatures for temperature sensing on a single smartphone. Chirp mixing is utilized to estimate the time differences and consequently the propagation speed of sound, which has a linear relationship with temperature. A median measurement accuracy of 0.3°C is reported in [16].

C. Solutions Enabled by Channel Characteristics

In this section, we present applications that detect gestures or motions that induce specific characteristics in over-the-air or structure-borne channels. All approaches in this section are device-free.

1) Over-the-air Channel Based Approaches: Presence of objects and changes in their shapes and positions in the air affect the channel characteristics and subsequently the reflected acoustic waves.

Gesture recognition: Gesture recognition aims to understand the expressive meaning of body parts, in particular hands, serving as an interface for humans to interact with smart devices. Previous approaches [79] often rely on dedicated devices or computationally intensive image processing techniques. In contrast, acoustic sensing methods are comparatively much more lightweight. The primary principle of these gesture recognition system is to decipher an appropriate CSI to accurately model acoustic features shadowed by a performed gesture. The key challenge lies in the discovery of this CSI (Challenge-IX). To evaluate the performance of a gesture recognition system, one often utilizes the detection or recognition accuracy that is defined by the ratio between the number of correctly recognized gestures and the total performed ones. We hereby present existing works on gesture recognition.

SoundWave [43] utilizes Doppler effect as CSI for gesture recognition. SoundWave continuously triggers an inaudible tone and infers gestures by sensing the spectrum of hand-reflected echoes. The key idea is that the reflected acoustic echoes from a moving hand are shifted in the frequency domain compared with the transmitted one. If the hand is moving away, the spectrum of the acoustic echoes is below the transmitted one and vice versa. Combining unidirectional movements allows the recognition of more complex gestures such as flick and quick taps. SoundWave reports recognition accuracy over 86.67% in various testbeds. AudioGest [105] applies both Doppler effect and multipath profiles for fine-grained gesture recognition. It combines both MD (Doppler frequency estimation) and DD approaches (multipath profiles based linear classifier). AudioGest reports an accuracy of 96% in detecting six hand gestures. Another Doppler based gesture recognition system is presented in [150]. This gesture recognition system, called EchoWrite, is an input system based on active acoustic sensing. EchoWrite decomposes the writing gestures into different strokes that exhibit different Doppler profiles estimated from acoustic reflections. Given that an English letter can be generated only by a unique combination of different strokes, a Bayesian inference model is exploited to decipher the written letters via acoustic profiles built on reflections.

UltraGesture [65] utilizes FHSS modulated signals to estimate the CSI in a similar vein with common wireless systems. After then, the estimated CSI is then act as input for a deep learning network for gesture classification. The underlying premise is that using CSI as input can preserve all important information while common methods built on Doppler frequency or multipath profiles would lose many critical information. As a result, UltraGesture can recognize 12 gestures with an accuracy over 97%. A similar approach can be found in [125] that achieves an recognition accuracy of 98.4% with up to 15 gestures. Other gesture recognition systems include VSkin [52] that enables gesture recognition on the back of a device and the work in [111] that facilitates depth-aware finger tapping on virtual displays. These two are based on the gesture tracking technology in [122]. VSkin achieves an accuracy of 99.65% in recognizing tapping events and the work in [111] reports a 98.4% finger tapping detection accuracy.

Speaker authentication: Besides gesture recognition, over-the-air channels can be also exploited for speaker authentication. Commonly used approaches that utilize speech signatures unique to individuals but do not test the “liveliness” of the speech. Thus, they can fall victims to replay attacks. SpeakPrint is a lipreading technology based on acoustic sensing [31]. It captures how a user speaks by recording mouth and vocal movement through near-ultrasound signals emitted by a mobile phone at the same time. By features extracted
from voice signals and reflected near-ultrasound signals, 100% accuracy is achieved in detecting replay attacks. For user verification, the authors report an average true positive rate of 99.56% and a false positive rate of 0.013%.

**Novel interactive controls:** The work discussed so far concerns the open air channel between a pair of acoustic speaker and microphone on a smartphone. Acoustic conduits [57] take a very different approach. It fabricates a tube as an acoustic conduit that connects the transceivers on a commodity smartphone. The tube has a physical control unit that can move and thus manipulates the properties of received acoustic signals. Through a fingerprinting strategy, the relationship between physical control and received acoustic features can be thus built. The authors developed a classification model to recognize different control commands and achieves 99% accuracy. Though being innovative and effective, this proposal cannot address **Challenge-IV** and **Challenge-X**.

2) **Structure-borne Channel Based Approaches:** Recalled that in Section II-B that, structure-borne signals in solid medium exhibit two properties, namely, acoustic dispersion and acoustic resonance. The acoustic dispersive property carries range information hence are often used for localization. The acoustic resonance property often reveals rich acoustic features and are more common in interactive applications. We now present respective applications built on structure-borne channel properties.

UbiTap [53] is a keystroke localization system built on a special physical property of structure-borne acoustic signals, called acoustic dispersion. The key observation in UbiTap is that the range information can be precisely obtained by the slope of a straight line shaped between frequency and time in the spectrogram of passively captured keystroke sounds. With this parametric model, they achieve millimeter-level keystroke localization performance.

ForcePhone [114] estimates applied forces on smartphones with built-in acoustic sensors by exploiting structure-borne sound propagation. It utilizes the fact that emitted acoustic signals from the speaker of a smartphone can cause vibrations of the phone body, the intensity of which is inversely proportional to external pressure. Based on this observation, it builds a close-form parametric model between applied forces and received signal intensity levels. ForcePhone reports a mean square error of 54g at stationary case, which is sufficiently low compared with the maximum 1.5 kg sensing range.

Touch & Active [91] utilizes a data-driven approach that leverages the acoustic resonant property to recognize different touch gestures as well as touch force. The basic idea is that a certain object has a unique resonant frequency and any touch action can alter it. Such a change manifests itself in the power spectrum of received signals with identifiable features hence can be recognized. This work reports an accuracy of 99.6% and 86.3% in recognizing five touch gestures and six hand postures on a plastic toy. Meanwhile, it can recognize discrete touch force with per-user recognition accuracy as high as 99.6%.

3) **Research Opportunities:** As mentioned in both **Challenge-IV** and **Challenge-X**, platform diversity can be particularly detrimental to system performance as it requires constant calibration. To ease the pain, building calibration agnostic parametric models is important. However, as acknowledged in **Challenge-IX**, it requires sophisticated domain knowledge and is remarkably challenging. Alternatively, one can leverage deep learning techniques that have shown promising results in generalizability. Techniques such as adversarial training [78] allow a model to generalize well on even unseen data, while few-shot learning techniques [126], [147] only require limited labels to quickly adapt on target environments. Some early attempts in this direction has been made. For example, the authors in [32], [39] employ meta learning [34], a kind of shot learning technique, to facilitate cross-device mobile sensing with only one or two data instances. We envision that more sophisticated deep learning approaches will be incorporated in acoustic sensing based on channel characteristics to address device, environment or subject diversity.

V. **FUTURE DIRECTIONS**

In the previous sections, we have highlighted unique research opportunities in different categories of acoustic sensing applications. In this section, we discuss a few research directions that we believe are under-investigated or are emerging in acoustic sensing in the future.

A. **Privacy and Security Threats**

The ever increasing applications of acoustic sensing also bring about many privacy and security issues. For instance, a recent study on acoustic sensing found that a recording system can act as an acoustic mixer [103], making it possible to detect ultrasonic signals above 24kHz on commodity mobile devices with no more than 48 kHz sampling rate. This phenomenon, caused by the non-linearity of acoustic sensors, has been exploited in jamming and communication [103]. The interesting finding can lead to innovative applications. However, such a technology also poses security threats on smart IoT devices with on-board microphones such as Google Home [48] and Amazon Echo [129]. It allows synthesizing audio signals audible to humans to manipulate such devices [145], [104] and thus open doors to malicious attacks. Additionally, existing work on keystroke detection [149], [69], [119] can pose privacy threats if enabled by malicious attackers with the knowledge of legitimate users. Therefore, techniques to detect and defend against such attacks constitute an important area of investigation for acoustic sensing.

B. **Repurposing Other Sensors for Acoustic Sensing**

In addition to use acoustic sensors for non-conventional purposes such as touch sensing and gesture tracking, it is possible to use other sensors to capture acoustic signals. For instance, the authors from [127], [134] and [107] exploit RF-radar and Lidar sensor to hack audio content, respectively. The key observation is that acoustic signals originate from vibrations, which can be detected through sensors that measure displacement. A main benefit of cross-technology sensing is that these non-dedicated acoustic sensors are immune to background acoustic noise and thus provide high SNR signals...
as long as the sampling rate is adequate. Therefore, an interesting research direction is to incorporate data from multiple sensing modalities to enable sophisticated sensing tasks or novel applications in adverse environments.

C. Earable Computing

With the prevalence of earable devices such as headsets and earbuds, many interesting new applications arise. Almost all earables come with on-board microphones and speakers, making them suitable for acoustic sensing. Additionally, newer devices such as Apple Airpods pro feature IMU sensors and force sensors. Fusing the measurements from multiple sensors opens up new areas of research. In [27], Choudhury provides an excellent overview of earable computing research opportunities. Notably, smart earables can be used to enhance human auditory perception in the form of hearing aids [30], binaural sound localization [130], and 3D spatial sound spatialization [138]. By characterizing the channel responses of inner ear canals, one can extract useful information for user authentication [36] or diagnosing ear infections [22]. From structure-borne signals and IMU sensor data, chewing and drinking activities can be monitored [63]. Structure-borne signals can also be used to enhance the recognition of one’s speech when air-borne signals are of poor quality in noisy environments. To realize these applications, in addition to common performance measures, it is important to minimize computation and communication overheads due to the limited form factor and battery lifetime of earable devices.

D. Benchmark Datasets and Platforms

To date, there is no open datasets or common platforms to benchmark acoustic sensing solutions. The lack of open datasets can be in part attributed to the need to design customized waveforms in specific applications. As discussed in Section II-A, hardware diversity among COTS devices render solutions tailored to one platform not suitable for others. Absence of common platforms also means that researchers often need to start from scratch and spend much time handling platform-dependent details such as programming languages and development frameworks. To overcome these problems, the acoustic sensing community can learn from successful practices in other communities. For instance, CRAWDAD is a wireless network data resource maintained by researchers at Dartmouth University with contributors from all of the world [5]. ORBIT [10] is a two-tier wireless network emulator/field trial designed to achieve reproducible experimentation, while also supporting realistic evaluation of protocols and applications. It is available for remote or on-site access by academic researchers both in the U.S. and internationally. GNURadio and USRP platforms provide unified hardware platforms and basic processing blocks for radio signal processing and propel research in advanced wireless technologies [7], [99].

Recognizing the need of common platforms, the work in [28] and [131] are among the first to build general sensing platforms on commodity mobile devices. Later on, the authors in [112] released a cross-platform support for ubiquitous acoustic sensing. Cai et al. develop ASDP, the first Acoustic Software Defined Platform, which encompasses several customized acoustic modules running on a ubiquitous computing board, supported by a dedicated software framework [17]. Unfortunately, these platforms have not yet gained much attraction in the community. We believe significant efforts are needed toward data sharing and advocate the adoption of common platforms for evaluation.

VI. Conclusion

This paper presented a systematic survey on acoustic sensing. We provided in-depth discussions on the unique challenges posed by acoustic hardware, systems and channels as well as techniques to mitigate them. We organized related research in a bottom-up manner from the physical layer to application-layer solutions to expose researchers and developers with a systematic view of what a full system entails. Discussions on research opportunities and future directions aimed to spawn further efforts in this area and encouraged the research community to take an concerned effort to transform research outcomes to real-world practices and products.

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