AcousticThermo: Temperature Monitoring Using Acoustic Pulse Signal

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***Abstract*—Temperature is an important indicator for agriculture irrigation, industrial manufacture, food safety, etc. While temperature measurement can be achieved via dedicated sensors, there still have a demand to sense temperature with ubiquitous computing devices. In this paper, we propose to enable the sound signal to measure the air temperature using commodity acoustic devices. Different from existing FMCW and OFDM based acoustic sensing system, we are the first to employ acoustic pulse signal and get rid of offsets to obtain the accurate sound speed. Then we precisely obtain temperature by quantifying the relation between sound speed and temperature. We build a temperature monitoring prototype named AcousticThermo, and conduct extensive experiments. Experimental results show that the proposed system can achieve an average estimation error of below $0.2^{\circ}C$ in various temperature environments.**

***Index Terms*—Temperature, Acoustic sensing, Contactless sensing, Sound speed**

I. Introduction

Temperature monitoring has a wide range of applications, such as weather forecasting [1], agriculture irrigation [2], machine/equipment temperature control [3] [4], and daily health care [5] [6]. For example, there are important instruments and equipments in the server room. Their running quality directly is affected by the ambient air temperature during operation. IT companies also have tens of thousands of computers that work for more than 10 hours a day, and CPU overheating may bring certain safety risks. The temperature monitoring is able to detect the temperature of the computer in real time, and alarms when exceeding the standard temperature to ensure the normal operation. Another example comes from the agriculture scenario, temperature has practical effects on the growth of crops. Too high or low temperature will affect the normal growth of crops, and even cause crops to die in severe cases. Therefore, there is a demand for cheap and stable measurement of temperature to help the crop growth. However, it is non-trivial to integrate temperature sensing capability into a ubiquitous computing device. Existing thermometers rely on the thermal expansion and contraction principle to sense temperature, it is designed that solids, liquids or gases undergo temperature changes under the influence of cold and heat. The commonly-seen thermometers include mercury thermometers [7], gas thermometers [8], alcohol thermometers [9], etc. However, the dedicated measurement devices cannot be integrated with the daily used devices, such as mobile phones or laptops.

Inspired by the recent acoustic contactless sensing technique, the ultrasound signals can be used to boost many applications, ranging from indoor localization [10] [11] [12], gesture recognition [13] [14] [15], gait recognition [16] [17], breathing estimation [18] [19] [20] and lip-reading recognition [21]. We note that the speed of sound changes with the air temperature. The lower the temperature, the higher the density of molecules in the air, so the speed of sound will decrease. Different from the traditional temperature sensing principle, we explore whether the sound signals can be used to sense temperature?

In this paper, we utilize the acoustic pulse signal to sense the temperature by detecting the change of temperature on the sound propagation speed. Existing acoustic sensing system usually employ either OFDM [22] or FMCW signal [23] for contactless measurement. The system delay and sampling frequency offset severely hinder the absolute distance acquisition. These methods thus need complex calibration and still face unstable sensing performance. To address this issue, we propose to utilize the acoustic pulse signal to sense the air temperature. The pulse signal is transmitted in the form of square waves through the voltage setting. The signal arrives at the obstacle at a known distance and reflects back to the receiver. The signal flight of time can be measured based on the voltage change, and the sound speed can further be obtained. By accurately quantifying the relationship between sound speed and ambient air temperature, we thus calculate the real-time temperature accordingly. We build a temperature sensing prototype system, called AcousticThermo. AcousticThermo achieves a median estimation error of $0.16^{\circ}C$ and a 90-percentile of $0.35^{\circ}C$. Finally, our real experiments demonstrate the effectiveness in both high-temperature and low-temperature environments.

Our contribution are as follows:

- We are the first to employ the acoustic pulse signal on commodity hardware to monitor the air temperature.
- We propose a signal processing pipeline which can successfully detect sound speed changes at a granularity of centimeter per second, enabling subcentigrade temperature sensing.

- We have implemented AcousticThermo and conducted experiments studies to demonstrate the robustness of system under different environmental conditions.

The rest of the paper is organized as follows. We present the system design and methodology of AcousticThermo in Section 2. The experiments and evaluation are described in Section 3. We conclude our work in Section 4.

II. System Design of AcousticThermo

A. System Overview

In this section, we present an overview about the design of the proposed AcousticThermo system as Fig. 1 illustrates. AcousticThermo consists of two devices: an commodity acoustic sensor device [24] that transmits/receives pulse signals and a Raspberry Pi device [25] that processes the audio samples for temperature sensing.

To perform temperature sensing, the system contains two modules: the signal processing pipeline and temperature estimation. 1) the ultrasonic device is turned to transmit pulse ultrasonic signal. The obstacle in the environment is preset to reflect the signal back to the device. The microphone on the ultrasonic device receives the echo, which is used to infer the time of flight (ToF) of signal. 2) The raspberry Pi achieves the functionality of temperature estimation. Based on the ToF and measured distance, the system first calculates the speed sound. With the insight of a rigorous mathematical relationship that exists between the speed of sound and temperature, we derive the environment temperature with high sensitivity and accuracy. Next, we describe each module in detail.

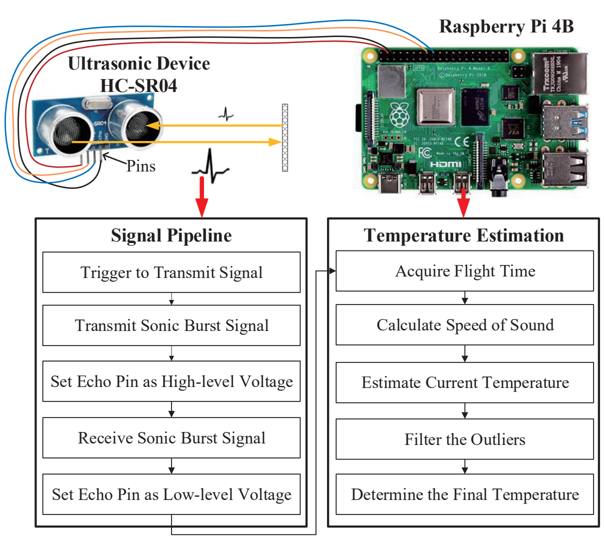


Fig. 1. System Overview of AcousticThermo

B. Signal Processing Pipeline

Traditional acoustic sensing systems usually exploit Frequency Modulated Continuous Wave (FMCW) [26] or Orthogonal Frequency Division Multiplexing (OFDM) signal [27] to indirectly estimate ToF and acquire distance. However, due to the central frequency offset and sampling frequency offset caused by unsynchronized clock in different devices, these approaches fail to estimate ToF with high accuracy. Fortunately, the pulse signal on the same device can overcome the above weaknesses and achieve accurate estimation of ToF. In this work, we employ HC-SR04 that integrates two ultrasonic transducers in the same PCB (Printed Circuit Board) to transmit and receive ultrasonic sound pulses. The left transducer of HC-SR04 in Fig. 1 acts as the acoustic transmitter, while the right transducer is the acoustic receiver.

As illustrated in Fig. 1, the four pins of HC-SR04 (from left to right) sensor are VCC, TRIG, ECHO, and GND, respectively. The VCC pin is for the power supply of the sensor and is connected to the 5V pin on the Raspberry Pi 4B. The TRIG pin is an input pin to trigger the ultrasonic sound pulses, while the ECHO pin is an output pin to produce a pulse when the reflected signal is received. Both of them are connected to the GPIO pins (e.g., Pin 16 and Pin 18) on the Raspberry Pi. GND pin is the ground pin that is connected to the ground pin of Raspberry Pi.

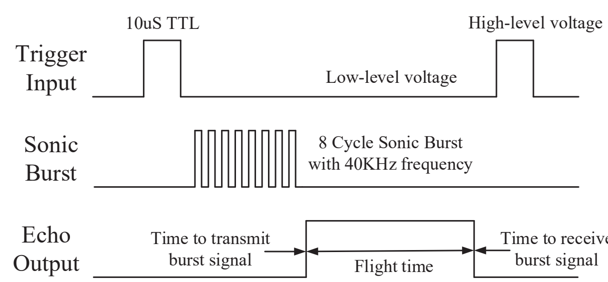


Fig. 2. Signal Processing Pipeline of AcousticThermo

Fig. 2 gives the signal timing diagram of HC-SR04, which shows the workflow of signal processing pipeline in AcousticThermo. Specifically, the steps are as follows:

1) The Raspberry Pi firstly supplies a pulse to the TRIG pin to trigger the sensor. The pause meets TTL (Transistor-Transistor Logic) signal standard requirement that is most commonly used to represent binary data. Namely, +5V stands for logic “1”, while 0V is equivalent to logic “0”. Unless otherwise specified, the signals below also accord with TTL standard. This is because TTL signal can achieve high speed transmission at both low cost and low power consumption. As we know, HC-SR04 sensor is only cost \$4 and the working current is only 15mA. The TRIG pin initially is at low-level voltage, then coverts to high-level voltage and lasts at least $10\mu s$, finally switches to low-level voltage again to generate the pause. The design of TRIG pin allows us to control the sensor to measure temperature on the basis of our wishes.
2) Once the complete pause is detected in TRIG pin, the sensor will automatically transmits a sonic burst of 8 pulses at 40KHz frequency. Meanwhile, the sensor raises its ECHO pin from low-level voltage to high-level voltage and records this timestamp as the beginning of the echo signal T_{start}. The reason employing 8 pulses

comes from two aspects: (i) 8 pulses can form a unique ultrasonic signature so that the receiver can differentiate the transmitted signal pattern from the ambient ultrasonic noise; (ii) it provides sufficient time to allow the receiver to detect the adequate number of pauses from the reflected burst signal. When the 8 ultrasonic pulses propagate through the air after sent by the transmitter, we continuously monitor the state of ECHO pin until a state transition occurs.

3) After the transmitter of the sensor sends out the sonic burst signal, the receiver of sensor will measure the echo-back signal with similarity. If the echo-back signal is received, the sensor will covert its ECHO pin from high-level voltage to low-level voltage. We record the timestamp of state transition as the ending of the echo signal T_{end}. Thus the pulse time width of ECHO pin is the time of flight for ultrasonic signal. Note that if the burst signal are not reflected back in case of on obstruction within the range of the sensor, the ECHO signal will timeout after $38ms$ and turn to low voltage. Then the sensor is ready for the next temperature measurement. AcousticThermo can achieve at least 25 measurements of temperature in one second.

Next we will explain how to estimate temperature with the acoustic sensor.

C. Temperature Estimation

The key module of AcousticThermo is to estimate the current temperature of indoor environment with the acoustic sensor. Note that the speed of sound in the air depends on environmental variables such as temperature. Thus before estimating the temperature, we first acquire the speed of ultrasound in the air. From the width of the received pulse in ECHO pin, the ToF can be calculated as:

$$\Delta t = T_{end} - T_{start} \tag{1}$$

Knowing that the propagation distance of ultrasound is d, then the speed of ultrasound c is:

$$c = 2d/\Delta t \tag{2}$$

For a number of practical scenarios, the distance can be measured in advance as the input of AcousticThermo. For instance, to measure the temperature inside a server, the ATX (Advanced Technology Extended) case provides standardized length, width and height. For the indoor environment, the distance between acoustic sensor and wall can also be easily measured. Specifically, we can place an obstruction in front of sensor at a fixed distance (e.g., 5cm) to manufacture a thermometer.

The relationship between speed of ultrasound and the temperature of transmission medium is as follow:

$$c = \sqrt{\frac{\gamma RT}{M}} \tag{3}$$

where c is the speed of ultrasound in the air, γ is the heat capacity ratio, R is the gas constant, T is the absolute temperature of gas, and M is the gas molecular weight. While Equation 3 can accurately relate the speed of ultrasound to both temperature and the air parameters, it is not easily to directly estimate temperature from ultrasound speed. To simplify the formulation, we employ the following equation to calculate the temperature.

$$T = (c - 331.3)/0.606 \tag{4}$$

where the temperature T is measured in degrees Celsius (°C), and the ultrasound speed is measured in m/s. The Equation 4 is accurate enough for our measurements, i.e., in the room temperature range (e.g., -15$°C$-50$°C$). Plugging the ultrasound speed in Equation 2, temperature can be calculated using Equation 4.

However, due to the interference from noise in the indoor environment, the measured temperature is also infected. To achieve accurate and stable temperature estimation, we employ a least-square smoothing filter named Savitzky-Golay filter [28] to smooth the estimated temperature. The filter takes advantage of linear least square method to fit successive subset of adjacent data points with a polynomial. After filtering the outliers, we finally identify the correct temperature value.

III. Evaluation

A. Experiment Setup

We have implemented AcousticThermo on a commodity cheap acoustic sensor (i.e., HC-SR04), and a Raspberry Pi 4B module, as shown in Fig. 3. The acoustic sensor converts the electrical signal into 40 KHz ultrasonic sound pulses. The receiver listens for the transmitted pulses. The detailed settings of the sensor are shown in Table. 1.

TABLE I
SPECIFICATIONS OF THE ACOUSTIC SENSOR

Operating Voltage	DC 5V
Operating Current	15mA
Operating Frequency	40KHz
Max Detection Range	4m
Min Detection Range	2cm
Measuring Angle	15 degree
Trigger Input Signal	$10\mu s$ TTL pulse
Dimension	45 × 20 × 15mm

The Raspberry Pi is used for signal processing and inferring the temperature. We develop an Android app to visualize the temperature monitoring results as shown in Fig. 4. The user can employ this app to preset the acoustic sensor distance, obtain the instantaneous temperature data, and monitor the whole day (recent 12hours) temperature changes. To measure ground truth values, we utilize an Raspberry Pi compatible module with dedicated temperature measurement device named DS18B20, which can measure temperature between $-10°$ and $85°$ achieving $\pm 0.5°C$ accuracy.

B. Performance Evaluation

In the experiments, we consider three typical scenarios, i.e., a room with natural temperature, a high temperature server

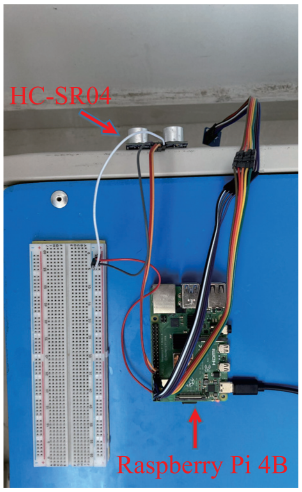


Fig. 3. AcousticThermo Testbed.

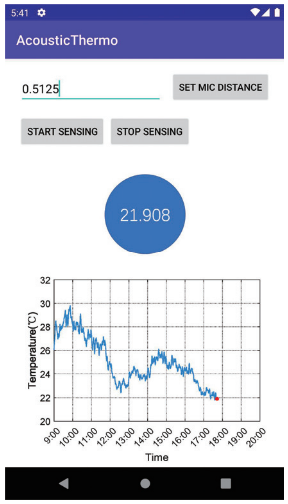
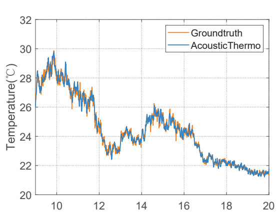


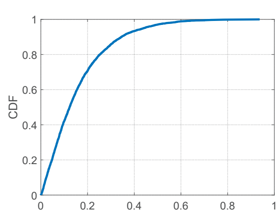
Fig. 4. A Snapshot of the App.

room and a cold air conditioning room. We design these experiments to show the effectiveness of the system, and use different room temperature to verify the robustness of system.

All day long room temperature monitoring. To measure the temperature change in a whole day, we conduct the experiments in an ordinary room and estimate the accuracy of AcousticThermo. The temperature changes with different times of the day correspondingly. As shown in Fig. 5(a), the blue line is the temperature measured by our system, and the orange line is the result measured by a dedicated temperature sensor device. We can observe that the temperature is highest around 10:00AM in the morning, reaching $29.8°C$, then the temperature decreases until 1:00PM. The reason is that it rains during this time. When the rain stops, the temperature increases again reaching to $26.1°C$ at 2:30PM in the afternoon. Subsequently, the temperature keeps dropping till the night. The average of temperature in a day is $24.4°C$. Our measurement results match the ground truth very well, and small changes in trends can be clearly captured. Fig. 5(b) depicts the CDF (Cumulative Distribution Function) of the estimated temperature. We can observe that AcousticThermo can achieve a median estimation error of $0.16°C$ and a 90-percentile of $0.35°C$ on our platform.



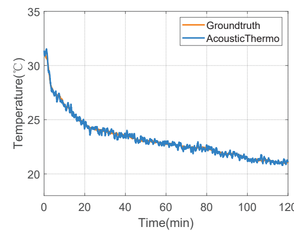
(a) All Day Measurements



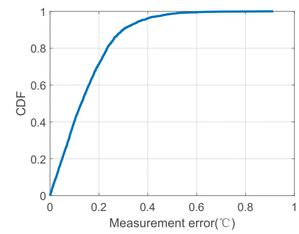
(b) CDF of All Day

Fig. 5. Temperature Measurements in a Whole Day

Low temperature detection in a cold room. In this experiment, we turned on the air conditioner to cool the room for 120 minutes. The initial temperature of the room is $31.4°C$. As air conditioning is cooling the room, the temperature of the room decreases, and finally drops to $21.0°C$. We observe that in the first 20 minutes, the room temperature drops significantly due to the continuous cold air. After the indoor temperature drops to $24.5°C$, the temperature begins to slowly decline. In the following one hour and 40 minutes, the temperature only drops by $3.5°C$, which can be used to automatically guide the air conditioner setting to improve the cooling efficiency. Fig. 6(b) shows the CDF of the estimated temperature. We also observe that AcousticThermo can achieve a median estimation error of $0.15°C$.



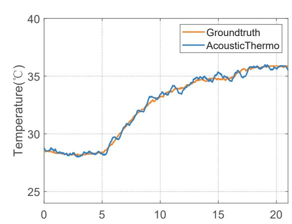
(a) Low Temperature Measurements



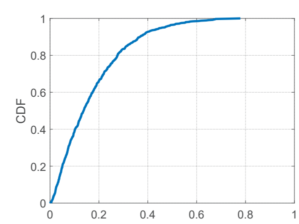
(b) CDF of Low Temperature

Fig. 6. Temperature Monitoring in a Low Temperature environment

High temperature detection in a server room. Now we place our AcousticThermo testbed in a server room for 20 minutes. As we know, the temperature of server room is usually high compared to the ordinary room. As shown in Fig 7(a), in the first five minutes, we measure the temperature outside the server room which is stable at $28.3°C$. After entering the server room, the temperature measured by our system quickly rises from $28.3°C$ to $35.9°C$, which fully demonstrates the sensitivity of the system. As shown in Fig. 7(b), we also observe AcousticThermo can achieve a 90-percentile of $0.37°C$.



(a) High Temperature Measurements



(b) CDF of High Temperature

Fig. 7. Temperature Monitoring in a Server Room

IV. Conclusion

In this paper, we propose AcousticThermo, the first temperature measurement system using acoustic pulse signal on a cheap and low-power ultrasonic sensor. The system only utilizes one ultrasonic sensor to continuously monitor temperature in indoor environment with high accuracy and sensitivity. The experiments lasted all day long demonstrate AcousticThermo achieves a median error of 0.16°C and a

90-percentile of 0.35°C. The comparable sensing results can be achieved in both low and high temperature environment, indicating the robustness of AcousticThermo.

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REFERENCES

[1] L. Al-Matarneh, A. Sheta, S. Bani-Ahmad, J. Alshaer, and I. Al-Oqily, "Development of temperature-based weather forecasting models using neural networks and fuzzy logic," *International journal of multimedia and ubiquitous engineering*, vol. 9, no. 12, pp. 343–366, 2014.

[2] M. Roopaei, P. Rad, and K.-K. R. Choo, "Cloud of things in smart agriculture: Intelligent irrigation monitoring by thermal imaging," *IEEE Cloud computing*, vol. 4, no. 1, pp. 10–15, 2017.

[3] T. Heath, A. P. Centeno, P. George, L. Ramos, Y. Jaluria, and R. Bianchini, "Mercury and freon: temperature emulation and management for server systems," *ACM SIGOPS Operating Systems Review*, vol. 40, no. 5, pp. 106–116, 2006.

[4] Y. Liang, Y. Mei, Y. Yang, Y. Ma, W. Jia, and T. Wang, "Low-coupling method in sensor-cloud systems based on edge computing," *Journal of Computer Research and Development.*, vol. 57, no. 3, pp. 639–648, 2020.

[5] L. Díaz-Rodríguez, M. Arroyo-Morales, C. Fernández-de Las-Peñas, F. García-Lafuente, C. García-Royo, and I. Tomás-Rojas, "Immediate effects of reiki on heart rate variability, cortisol levels, and body temperature in health care professionals with burnout," *Biological Research for Nursing*, vol. 13, no. 4, pp. 376–382, 2011.

[6] F. Zhang, K. Niu, J. Xiong, B. Jin, T. Gu, Y. Jiang, and D. Zhang, "Towards a diffraction-based sensing approach on human activity recognition," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 3, no. 1, 2019.

[7] M. Board, "Comparison of disposable and glass mercury thermometers." *Nursing times*, vol. 91, no. 33, pp. 36–37, 1995.

[8] F. Pavese and G. M. M. Beciet, *Modern gas-based temperature and pressure measurements*. Springer Science & Business Media, 2012.

[9] D. Camuffo and A. Della Valle, "A summer temperature bias in early alcohol thermometers," *Climatic Change*, vol. 138, no. 3-4, pp. 633–640, 2016.

[10] A. Wang and S. Gollakota, "Millisonic: Pushing the limits of acoustic motion tracking," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, ser. CHI '19, 2019, pp. 1–11.

[11] R. Jia, M. Jin, Z. Chen, and C. J. Spanos, "Soundloc: Accurate room-level indoor localization using acoustic signatures," 2015, pp. 186–193.

[12] F. Zhang, Z. Chang, K. Niu, J. Xiong, B. Jin, Q. Lv, and D. Zhang, "Exploring lora for long-range through-wall sensing," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 4, no. 2, 2020.

[13] Y. Xie, F. Li, Y. Wu, S. Yang, and Y. Wang, "D3-guard: Acoustic-based drowsy driving detection using smartphones," 2019, pp. 1225–1233.

[14] S. Cao, P. Yang, X. Li, M. Chen, and P. Zhu, "ipand: Accurate gesture input with smart acoustic sensing on hand," in *2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, 2018, pp. 1–3.

[15] K. Niu, F. Zhang, Y. Jiang, J. Xiong, Q. Lv, Y. Zeng, and D. Zhang, "Wimorse: A contactless morse code text input system using ambient wifi signals," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 9993–10 008, 2019.

[16] W. Xu, Z. Yu, Z. Wang, B. Guo, and Q. Han, "Acousticid: Gait-based human identification using acoustic signal," 2019, p. 25.

[17] J. Huang, F. Di Troia, and M. Stamp, "Acoustic gait analysis using support vector machines." in *ICISSP*, 2018, pp. 545–552.

[18] T. Wang, D. Zhang, Y. Zheng, T. Gu, X. Zhou, and B. Dorizzi, "C-fmcw based contactless respiration detection using acoustic signal," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 1, no. 4, 2018.

[19] F. Zhang, D. Zhang, J. Xiong, H. Wang, K. Niu, B. Jin, and Y. Wang, "From fresnel diffraction model to fine-grained human respiration sensing with commodity wi-fi devices," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 1, 2018.

[20] K. Niu, F. Zhang, J. Xiong, X. Li, E. Yi, and D. Zhang, "Boosting fine-grained activity sensing by embracing wireless multipath effects," in *Proceedings of the 14th International Conference on Emerging Networking EXperiments and Technologies*, ser. CoNEXT '18, 2018, p. 139151.

[21] L. Lu, J. Yu, Y. Chen, H. Liu, Y. Zhu, Y. Liu, and M. Li, "Lippass: Lip reading-based user authentication on smartphones leveraging acoustic signals," in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 2018, pp. 1466–1474.

[22] R. Nandakumar, V. Iyer, D. Tan, and S. Gollakota, "Fingerio: Using active sonar for fine-grained finger tracking," in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, ser. CHI '16. New York, NY, USA: Association for Computing Machinery, 2016, p. 15151525.

[23] C. Cai, H. Pu, M. Hu, R. Zheng, and J. Luo, "Sst: Software sonic thermometer on acoustic-enabled iot devices," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2020.

[24] "Ultrasonic distance sensor - hc-sr04," https://www.sparkfun.com/products/15569.

[25] G. Halfacree, "Raspberry pi 4 now comes with 2gb ram minimum," in *The MagPi (91). Raspberry Pi Press.*, Retrieved 28 May 2020.

[26] J. Zheng, *Optical Frequency-Modulated Continuous-Wave (FMCW) Interferometry*, ser. Springer Series in Optical Sciences. Springer, 2005. [Online]. Available: https://books.google.com/books?id=b9vz97IrRa8C

[27] W. Kabir, "Orthogonal frequency division multiplexing (ofdm)," in *2008 China-Japan Joint Microwave Conference*, 2008, pp. 178–184.

[28] R. Schafer, "What is a savitzky-golay filter? [lecture notes]." in *IEEE Signal Processing Magazine*, vol. 4, no. 28, July 2011, p. 11117.