Toward a wearable crowdsource system to monitor respiratory symptoms for pandemic early warning

Zhang, Wei; Li, Jie; Wen, Yonggang; Luo, Yong

2021

Zhang, W., Li, J., Wen, Y. & Luo, Y. (2021). Toward a wearable crowdsource system to monitor respiratory symptoms for pandemic early warning. IEEE Network, 35(3), 56-63.
<https://dx.doi.org/10.1109/MNET.011.2000718>

<https://hdl.handle.net/10356/152737>

<https://doi.org/10.1109/MNET.011.2000718>

© 2021 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. The published version is available at:
<https://doi.org/10.1109/MNET.011.2000718>.

Downloaded on 26 Apr 2023 21:58:08 SGT

Towards A Wearable Crowdsourcing System to Monitor Respiratory Symptoms for Pandemic Early Warning

Wei Zhang, *Member, IEEE*, Jie Li, Yonggang Wen, *Fellow, IEEE*, and Yong Luo

Abstract—Early warning of a potential pandemic with respiratory symptoms is crucial for global health management. It enables timely intervention to reduce the likelihood of uncontrollable massive virus spread. In this research, we propose to leverage the ubiquitous wearable devices to develop a wearable crowdsourcing system to monitor respiratory symptoms such as cough and fever. Wearable devices nowadays can directly and non-intrusively measure people's vital signs in real-time with a variety of sensors embedded. We collect the data from wearable devices and develop machine learning algorithms to analyze the data for respiratory symptom monitoring and early warning. In particular, we focus on cough detection through multi-source data fusion (e.g., accelerometer amplitude and microphone audio). Preliminary results show that our algorithms result in higher detection accuracy and less false positive with the least use of computing resources. This research potentially transforms the way the pandemic early warning is implemented and the way we respond to public health crises in the years to come.

Index Terms—Crowdsourcing; wearables; public health; artificial intelligence; edge computing; respiratory symptom.

I. INTRODUCTION

COVID-19 has changed and will dramatically change our human society. Millions of people are infected in this pandemic, and thousands of them die every day. The entire world is in panic. The current impact is widespread and there is no foreseeable end. Today, the world's health system is overloaded for healthcare professionals and medical institutions. The global economy is at a deadlock with a high unemployment rate and endangering industrial sectors. People's daily life and social activities are highly disrupted with cancellation, restriction, and undue stress among the population. We are fighting the pandemic to restore the way

forward. However, unfortunately, the effective and widely accessible vaccines are not yet available, and even the testing has not been scaled up to a satisfying level [1].

One promising approach is to have an early warning system. For people who have been in close contact with the coronavirus and have suspicious respiratory symptoms (e.g., cough, fever, etc.), testing should be given priority to take advantage of insufficient testing capacity. Once detected to be positive, say virus carriers, they, as well as their close contacts, should be isolated from people, and appropriate and timely treatment measures should be taken to cut off the chain of infection until they fully recover [2]. The benefits of early intervention are manifold. With the significant reduction of infection and transmission, the health system is unlikely to be overloaded, economic activities can be restored on a larger scale, and our daily lives will be less disrupted, thereby promoting the well-being of the entire society.

Existing efforts include medical and non-medical measures. The former has advanced high-precision technology, but the cost is also high. A brute force method is the city-wide testing like China did in the mega-cities like Wuhan and Beijing. This method is only feasible with astonishing mobilization ability and huge cost. However, for many cities and countries, this approach is either impractical or unsustainable. In addition to testing, some countries such as the United States also require data-driven surveillance systems that collect data on morbidity, prevalence, hospitalizations, and deaths related to the pandemic. The collected data will be managed by the government for further data visualization and analysis, contact tracking, and disease impact assessment. The huge cost of medical-based methods has prompted non-medical solutions. Some countries (such as Singapore) use Bluetooth-enabled devices (such as existing smartphones and inexpensive tokens) to enhance contact tracing. In addition to basic digitization, data is also a valuable source of revealing some useful insights. For example, Google uses real-time search queries and allows individuals to report any respiratory symptoms online. Then, the data is analyzed and the areas with a high percentage of symptom activity are displayed to the public in real-time to complement the relatively slow traditional processing methods. Although these solutions are cost-effective, they lack the accuracy and rigor inherent in medical methods. In fact, it is difficult to achieve a tradeoff between accuracy and cost in the above two types of methods.

In recent years, wearable devices have been widely adopted and the upwards trend is clear for the years to come. In this

Manuscript received January 1, 2000; revised January 1, 2000; accepted January 1, 2000. This research is funded by National Research Foundation (NRF) via the Green Buildings Innovation Cluster (Grant NO.: NRF2015ENC_GBICRD001-012), administered by Building and Construction Authority (BCA) Singapore. In addition, this research is sponsored by National Research Foundation (NRF) via the Behavioural Studies in Energy, Water, Waste and Transportation Sectors (Grant NO.: BSEWWT2017_2_06), administered by National University of Singapore (NUS). Moreover, this research is funded by Nanyang Technological University (NTU) via the Data Science & Artificial Intelligence Research Centre @ NTU (Grant NO.: DSAIR@NTU).

W. Zhang is with the Infocomm Technology Cluster, Singapore Institute of Technology (SIT), Singapore 567739 (e-mail: wei.zhang@singaporetech.edu.sg.)

J. Li and Y. Wen are with the School of Computer Science and Engineering, Nanyang Technological University (NTU), Singapore 639798 (e-mail: jie006@e.ntu.edu.sg and ygwen@ntu.edu.sg.)

Y. Luo is with the Institute of Digital Media, Peking University, Beijing 100871, China (e-mail: yluo180@gmail.com.)

Fig. 1. The system architecture of the proposed wearable crowdsourcing system for respiratory symptoms monitoring and early warning with three layers, namely, sensing layer, communication layer, and application layer.

paper, we argue that it is technically feasible to establish a global pandemic monitoring and tracking network out of the wearable network fabric. Wearable devices provide raw data collection and multi-sensor fusion. Specifically, wearables can directly measure people's vital state, which is traditionally unavailable except using costly medical instruments. The directly measured real-time data can be further processed and analyzed by the latest artificial intelligence (AI) technologies, i.e., for the respiratory symptoms-based infection prediction. Accordingly, we can achieve the optimal tradeoff between cost and accuracy supported by wearable and AI technologies.

In this research, we propose using crowdsourcing methods and develop a minimal viable product (MVP) with tailored algorithms for data analytics. The MVP first leverages the emerging wearables to monitor people's vital signs (e.g., skin temperature, heartbeat rate, etc.). The data can be analyzed in a centralized or distributed fashion, and people with respiratory symptoms like coughing can be detected early and timely. Once a suspicious case is found, the MVP will immediately trigger the follow-up actions like quarantine, testing, and medical treatment. In this way, the potential negative consequences of the case can be minimized.

Among the typical respiratory symptoms, some can be measured directly or easily, like fever, while some others do not own such an advantage and mostly rely on medical approaches. In this article, we are particularly interested in cough, a common upper respiratory tract symptom, which, however, lacks and urgently needs an automatic and cost-effective solution to monitor and detect. Here, we creatively study the feasibility of using the embedded accelerometer and microphone, widely available in nowadays wearables. We detect cough based on the amplitude of the accelerometer and the audio signal of the microphone. To validate our idea, we collect the multimodal data corresponding to various daily activity scenarios, like sleeping, working, mild coughing, severe coughing, and even boxing, with both accelerometer and microphone records. We apply a two-stage AI-driven algorithm to analyze the multimodal data and have successfully proved the effectiveness of our system through preliminary experimental study.

Our investigation in this research establishes a cost-effective

and highly reliable system for respiratory symptom monitoring and early warning. While our research is motivated by the COVID-19 pandemic, its applications and impact can be far beyond this scope. For example, influenza breaks out once a year or even multiple times a year. It has a series of common respiratory symptoms as COVID-19 and potentially can also use our system. COVID-19 has been devastating to our world this year, but we all know this is not the last pandemic for mankind. Countries that experienced the SARS epidemic about twenty years ago have generally performed well this year in responding to the pandemic. The key reasons lie in the well-prepared mentality as well as the technologies. We believe the benefit of our system is not limited to dealing with this pandemic. In the long journey ahead of the human race, it will help us be more prepared and equipped and finally overcome the coming pandemics.

II. SYSTEM ARCHITECTURE

We present the system architecture and the related discussions of the wearable crowdsourcing system for respiratory symptoms monitoring and early warning in this section. An illustration of the system architecture is shown in Fig. 1 with the following three building blocks for sensing, communication, and application.

A. Sensing Layer

Nowadays, various consumer electronics have penetrated people's daily life. Wearable devices and smartphones are becoming more and more common, especially for the residents in developed nations like Singapore. Sensors with different functions are embedded into the latest commodity wearables. Popular ones, take Microsoft (MS) Band 2 for example, include heartbeat rate sensor, accelerometer, GPS, microphone, ambient light sensor, skin temperature sensor, and so on. Those sensors generate abundant multimodal data to reflect people's vital states and support further monitoring and analysis.

1) *Wearables*: In this work, we propose to utilize both wearables and smartphones. The former serves as the frontline of monitoring and collecting the real-time environmental state and vital signs in a non-intrusive fashion. We choose the MS

Band 2 wristband with the aforementioned extensive sensing functions and complete API support. By default, the collected data is automatically saved in the embedded storage of the wristband. Then the data I/O is facilitated through the provided APIs, like extracting the sensor data.

We realize that the off-the-shelf wristbands with remarkable sensing capabilities and API support are expensive, for example, the introductory price of MS Band 2 is \$250. Therefore, we also explore the possibility of using the original equipment manufacturer (OEM) products at a steeply decreased price. Our recent exploration and testing have validated our concept and the feasibility of reducing the cost by almost 90%, i.e., \$25 for each OEM wristband as shown in Fig. 2, with the monitoring performance on par with the commercial ones. Please note that our exploration is only for small-scale purchases. If the OEM wristbands are purchased in large quantities, the unit price will be even lower. In view of the controllable cost, companies and organizations can use our system to carry out early and accurate detection of respiratory symptoms without the concern of a large bill. Besides, OEM also offers the benefit of flexibility. Wearables can be highly application-specific with sensors properly chosen regarding the aspects like accuracy, energy-efficiency, and price. Also, OEM wearable owners are granted more data access privileges without having the 3rd party companies control or limit the access and uninterrupted data access enables stable services.

2) *Mobile Application*: Wearables are normally worn near the surface of the skin, so data sensing can be direct and accurate. However, due to the limitation of size and lightweight, the wearable device is not an ideal place for computing and visualization. Therefore, we supplement the wearables with a smartphone or an edge server, with a much larger screen as well as computing and storage capabilities. We have specially developed a mobile application for user information management and data visualization. Some of its functions are derived from our previous projects on pervasive sensing in smart buildings [3]. The mobile application as shown in Fig. 2 allows the user to register for an account. Any data access requires the user to log in to the application first for security control. Once logged in, the gauge page will display the latest sensor data to the user.

The next development phase will also capture some other interesting functions in our mobile application. For example, we can add an interface for reporting respiratory symptoms to the related agencies or organizations, a reward page for motivating users to maintain good hygiene practice, and an application configuration page for settings like notification.

B. Communication Layer

The communication layer connects the sensing layer and the application layer. In a typical case, the wearable device collects sensor data and first saves the data in its local storage, which is normally small. Then, the device backs up the data (a large amount of raw data or a small amount of statistical information) to the host smartphone or a near edge server via Bluetooth or WiFi. Smartphones follow a similar scheme and support data communication with government agencies or

Fig. 2. Our in-house OEM wristband with extensive sensors and APIs and the mobile application for information management and visualization.

other responsible entities, and edge servers can also support wired communication. Generally, for data communications covering a wide geographical range, telecommunication services such as 5G/6G will be viable alternatives instead of near-field Bluetooth communication [4]. By accessing crowdsourced data, monitoring and early detection of respiratory symptoms can be realized through appropriate data processing and analysis in the host smartphone or centralized big data server.

Despite the mature communication technologies, the wearables do have some physical constraints. If they are not resolved properly, they potentially can become the bottleneck in the full-scale deployment of a system. A major limiting factor is the battery life, which is typically limited for the wearables. Normally, wearables can last for no more than a few days when fully charged, or even a couple of hours for heavy usage. The battery can be saved by reducing the frequency of data transmission and the amount of data. For frequency, the monitoring system should not require an always active transmission with a resolution of seconds or even milliseconds. For certain situations, the hourly data synchronization is sufficient with manageable battery usage. One alternative is to implement the event-driven triggers so that the transmission is only occasionally activated in response to certain events when necessary. For data volume, filters can be applied to keep only suspicious data and compression helps re-encode the original data with fewer bits. Please note that battery-saving cannot be achieved by concept alone and practical challenges must be solved as well. For example, OEM devices may not support

Fig. 3. Distinct accelerometer amplitude profiles for different scenarios with data sampled in 0.1-second resolution.

compression by default and APIs may only return raw data. Obtaining the required OEM firmware usually requires a lot of effort and cost, and these aspects should be fully reflected in system planning and development.

C. Applications Layer

The collected data can help realize various applications. In the field of respiratory symptoms, applications can be cough detection, fever detection, recovery plan, and so on. Among the symptoms, some can be directly reflected based on the data from one sensor. But more often the symptoms reside as the latent information among multiple data sources, and AI may play the role of extracting the latent information. We are dazzled by the excessive data we have, i.e., heartbeat rate and blood oxygen. The data from one sensor may be related to different symptoms, and the data is usually not the sole determinant. Existing practices highly rely on medical knowledge to specify a combination of sensor data and associate it with a certain symptom. Such a strong reliance on expertise and generally not easily accessible knowledge may hinder problem-solving. Meanwhile, existing knowledge is not comprehensive and data can be a critical source to explore new knowledge. Thereby, the crowdsourcing-based AI technology will become a key driving force for rapid, accurate, and cost-effective respiratory symptom monitoring and early warning.

Our system is data-centric and naturally brings us to the discussion for security and privacy. The requirements for security and privacy [5] as well as people's acceptance vary in different countries and different applications. From a non-technical perspective, some countries and companies enforce trace tracking and data reporting in such pandemics. Although data is anonymized before the data is sent out, privacy violations still occur, i.e., a person can be identified based on his/her

tracking records. The success of those practices ultimately depends on non-technical factors like acceptance and trust. In terms of the technical considerations, a promising solution is federated learning [6]. Personal data can be managed and processed in personal wearables and smartphones without being uploaded to an external party. The information flow of personal data is substituted by the AI model as a collective knowledge entity without personal identities. However, worth noting that the feasibility of such an idea needs us to get through the hardware capabilities like the computing power and function support as well as government policies.

III. COUGH DETECTION WITH MULTIMODAL DATA

In this part, we discuss the feasibility of intelligent cough detection with the data of different modalities, i.e., accelerometer amplitude and microphone audio. Let us first demonstrate the rationale for the usage of an accelerometer.

A. Accelerometer for Cough Detection

We show the accelerometer amplitude profiles under different scenarios in Fig. 3. As we can see, the experiment volunteer barely moves during sleep, and the accelerometer amplitude is almost zero. During normal office working hours, there are some vibrations, but more or less in the form of white noise with a very small amplitude.

The profiles become interesting in the unsteady scenarios. A mild cough can be reflected with slight spikes in the profile, and its amplitude is around twice that of a working scenario. For the time slots without cough spikes, the amplitude reflects the white noise in the normal state. A cough may be mild or severe. For the latter, we can intuitively foresee a big change in magnitude. In fact, judging from the profile of the severe cough, the spikes are many times higher than the normal state

Fig. 4. Our two-stage solution for cough detection based on the multimodal data. Accelerometer amplitude data is used in first stage to pick out the suspicious cough cases and the microphone audio data is analyzed in the second stage to finalize the detection.

amplitudes. A severe cough also lasts longer. While a mild one is short and takes around half second, a severe one can span over one second with a huge expulsion of air.

At this stage, we might wonder whether we can detect a cough from the normal working activities with an amplitude threshold. Unfortunately, the answer is no. While a cough is an intense action for humans, we should be aware that wristbands are distant from the action source like the neck and chest. The vibration propagates from the source to the wrist to be detected, and by then the signal attenuation makes it difficult to retain much of its original intensity. Some scenarios do have movements close to or even originated from the wrist, and the amplitude of those scenarios can be more pronounced without much attenuation. One such scenario is boxing, as we show in Fig. 3. We can see that the amplitude for boxing is even much higher than that of a severe cough. For easy comparison, the amplitude above a certain value is not displayed deliberately. Even after the punching, the amplitude is much higher than that of a mild cough.

Overall, we are able to observe that the accelerometer amplitude profiles are very different for each scenario, even in terms of the maximum and minimum amplitudes. Naturally, we shall investigate the possibility of using the monitored accelerometer amplitude to detect respiratory symptoms such as coughing. We believe that adopting our system on a large-scale requires us to consider different design aspects such as cost, accuracy, and battery sustainability. Therefore, in the next part, we present our design to capture those key aspects.

B. A Two-Stage Algorithm with Multimodal Data

In this part, we introduce our algorithm for cough detection. We first discuss the necessity of using multimodal data. Then we describe the algorithm and the present preliminary experimental results.

1) *Multimodal Data Motivation:* We propose to utilize multimodal data for cough detection. From the above part,

we understand that the accelerometer amplitude profile is correlated with a cough. However, such mono-modality data is insufficient for accurate detection. Cough can lead to the profile with certain patterns like the amplitude range. However, it is uncertain that those patterns are uniquely related to the cough scenario. This is especially true that there are countless scenarios available for a wristband and it is impractical to test or even list out all of them. We specifically show the profile of speaking in Fig. 3, and we can see the maximum amplitude is roughly the same as a mild cough. Therefore, the introduction of the data of the other modalities becomes a logical choice to compensate for the information deficit of the accelerometer amplitude data.

When it comes to coughing, the first thing we think of is the unique sound, which may not be the accelerometer vibrations we monitor in the wristband. Fortunately, sound in the form of audio data can be easily accessed from the microphone commonly found in wearables and smartphones. We thus utilize the audio data for cough detection and hope to maximize the benefits of both accelerometer data and audio data. On the bright side, audio data analysis is not unfamiliar to the research community and many advanced tools are already available for scenario detection, i.e., coughing and knocking. As such, we no longer need to reinvent the wheel for audio data analytics and can take advantage of the latest technologies. However, in terms of the imperfections, audio data is not a panacea. It is still challenging to always accurately detect a cough, and even with the correct detection, it is hard to tell who is coughing. Considering a microphone in a mass transportation environment, some passengers can be closer to a microphone than the owner of the microphone. Same as our thoughts on the accelerometer, audio data shall not be used alone for cough detection and we need the data of different modalities to reveal a complete picture.

Our MVP makes full use of the advantages of both accelerometer data and audio data and we strive to maximize the benefits of both data. The advantage of the accelerometer

is that it is closely attached to the human body. As long as a cough signal is detected, it is almost certain that the signal comes from the corresponding person. This direct correspondence may not be suitable for the audio signal, whose sound signals may come from different sources. However, audio data has been a common and popular data modality for a century and we do not lack the tools to process it. Thereby, our plan is to conduct the coarse-grained cough detection based on the accelerometer data and then trigger the fine-grained detection or verification on the audio data if necessary.

2) *Algorithm Description*: The illustration of our solution is shown in Fig. 4 with two major stages. We let the wristband monitor the accelerometer data in real-time. By default, we restrict the access of computing and communication units for cough detection to prolong the wristband battery lifetime. A simple threshold filter is implemented as a trigger, where the lower- and upper- thresholds are specified according to the cough amplitude profiles, i.e., 0.05 and 0.30, respectively. Taking the accelerometer amplitude as a time-series, once a segment of the time-series can pass through the filter, we treat it as an event that activates the trigger. This is the end of the first stage and the trigger directs the detection stream to the second stage, where the main focus is on the audio data.

Audio-based scenario detection involves heavy data processing and analytics, which are computational and power intensive. Thus, given the high chances indicated in the first stage, we perform the audio-based operations for cough detection in the second stage. In this way, by handling suspicious cases only occasionally, we can avoid consuming much power on computation and communication. Nevertheless, some scenarios such as conversations may still pass the first stage checkpoint. We activate the communication unit of the wristband and transfer the audio data to the host smartphone or edge server with stronger computing performance and battery capacity. Then, the smartphone or edge server processes the audio data and finds out the corresponding scenario. If a cough scenario, either mild or severe, is detected, our system will alert the human subject and take follow-up actions. Typical actions can be prompting an appointment message for medical-based testing and reporting to the national or regional respiratory disease center.

Note that our algorithm is based on the facts of wearables' limited computing and battery capacity as well as AI algorithms' high computational needs. The future may be different when wearables are less constrained by the processing and battery limitations and lightweight AI models are powerful and energy-efficient enough. By then, advanced multimodal learning can be performed in the wearables with multimodal data such as accelerometer amplitude profiles, blood pressure, and the heartbeat rate. With the features of different modalities lie in diverse spaces, we can employ neural networks to map the multimodal features into a common space with a loss function based on tensor canonical correlation analysis [7]. An auto-encoder can also be added to each modality during the space learning to maximally preserve the information of different modalities. Besides, the attention mechanism can help automatically assign a weight to differentiate the importance level of different modalities. Finally, we can aggregate the

TABLE I
COUGH DETECTION PERFORMANCE.

Cough	1st Stage		Cough	2nd Stage	
	True	False		True	False
Positive	6	4	Positive	6	0
Negative	96	0	Negative	4	0

mapped representations from multimodal data for respiratory symptom detection.

3) *Preliminary Results*: We present the preliminary experimental results of our MVP in this part. First, we collect a multimodal dataset to capture different scenarios. Each data entity in the dataset includes a start timestamp, an end timestamp, the accelerometer data as a time series, the audio data as a time series, and a scenario tag. In total, we have 106 data entities, each lasts for about six seconds. Among them, 6 entities are cough cases and the rest are not. We also down-sample the accelerometer data originally in a millisecond to the 0.1-second resolution to facilitate the data processing.

For each data entity, we apply our two-stage algorithm to it. In the first stage, we adopt the lower threshold of 0.05 and the upper threshold of 0.30 for our bandpass filter for the accelerometer amplitude data. Once the valid output signal is observed for at least three consecutive time slots in the first stage, we mark the entity as suspicious. The basic principle of our scheme is that coughing can last for a few tenths of seconds, so checking multiple consecutive time slots helps us avoid abrupt noises. After that, we process the suspicious entity and perform audio-based scenario detection based on the entity's audio data. Here, we adopt an AI-based plug-and-play real-time acoustic activity recognition tool Ubicoustics [8]. This tool can run on most popular platforms and has been trained and tuned based on a huge labeled audio dataset and its excellent detection performance has laid a solid foundation for our system. Worth mentioning that our system is not limited to a certain audio analytics tool, and the more advanced or specialized tools [9] can be integrated into the system in the future. Finally, after the detection, we verify the detection accuracy by checking the data entity's scenario tag. We expect that the cough entities can be detected accurately and meanwhile the system does not issue false alarms to the non-cough entities.

Table I shows the cough detection performance of the proposed two-stage algorithm on our collected dataset. In the first stage accelerometer-based detection, 10 out of 106 entities are detected to be positive (cough), where 6 are true positive and 4 are false positive. The results indicate a precision of $6/(6+4) = 0.6$, a recall of $6/(6+0) = 1$, and accordingly an F1-score of $2 * 0.6 * 1 / (0.6 + 1) = 0.75$. The 10 positive cases are considered suspicious and we perform the second stage audio-based detection for those cases. In this stage, 6 cases are confirmed to be true positive and the rest 4 are negative, indicating 4 false alarms in the first stage. It is worth noting that only about one in ten cases are processed in the second stage. Most cases are marked as safe in the first stage and exempted from further testing in the second stage. Given that the data processing and analytics are computationally intensive

with heavy communication overhead, our two-stage solution is cost-efficient in terms of resource usage. Overall, through our solution, we can successfully detect the cough scenarios in the preliminary experimental study with minimal cost overhead.

C. Discussion

We would like to discuss some interesting aspects of our proposed solution in this part. First, while multimodal data from accelerometer and microphone is shown to be effective in our preliminary experiments, we believe a wider range of data sources offers more abundant information, which is helpful to further improve the detection performance. For example, skin temperature from wearable sensors shall be correlated with body temperature and thus be useful for detecting fever, which is another key respiratory symptom. Activity level, perhaps measured in the number of steps, may also be an indicator that a person is not feeling well enough thus moving less [10]. Data sources can be diverse and not limited to wearables. Researchers recently use electronic patient-reported outcomes [11] and radio-based person identification information [12] to enhance the early respiratory monitoring system. Nevertheless, we would like to highlight that accuracy is not the only consideration for a practical system. Other aspects like battery life and analysis complexity also affect the choice and usage of data modalities.

Our preliminary study adopts fixed thresholds of the accelerometer amplitude profiles and the thresholds are possible to be fine-tuned and optimized. One direction is to explore region-based thresholds. For high-risk areas such as transportation hubs and healthcare institutes, thresholds shall be lower to drive a more vigilant monitoring system to avoid massive virus transmission. Another direction is to derive personalized thresholds, assuming that amplitude profiles are heterogeneous for different people. With more data collected in the future, a model specialized in the relationship between the user's vital characteristics and adaptive threshold can be trained. Once deployed in the wearables, the model can help derive the corresponding personalized thresholds. Here, we shall be noted that personal data brings the concerns like data privacy. Consider that wearable-based monitoring cannot and shall not be the last line of defense, the side effects and overhead may reduce the practicality of personalized thresholds.

IV. CONCLUSION

COVID-19 has profoundly affected the entire world and mankind, and the impact will continue for a long time. Existing approaches are either costly or inaccurate and sustainable solutions are essential for us to fight against the pandemic. In this research, we enable a cost-effective and accurate respiratory symptom monitoring system for pandemic early warning. We leverage the ever-popular pervasive sensing and wearable technologies and we design and implement a crowdsourcing-based system to monitor and detect respiratory symptoms.

Cough detection is specifically demonstrated. We utilize multimodal data (e.g., accelerometer amplitude and microphone audio) and propose a specialized two-stage detection solution. The preliminary results show that our solution is accurate in detecting cough without incurring much hardware cost and energy expenditure.

In the future, our system can be augmented and developed to be a more comprehensive and advanced system, i.e., with a high-level of security, privacy, and explainability. We also plan to carry on our multimodal data collection with multi-party collaboration and an optimized and standardized data collection scheme. With a sufficiently large dataset, we can validate the experimental performance in more detail, explore more on the advanced AI models, and contribute to the improvement of the existing tools like Ubicoustics. In the end, we believe that our system is not limited to the COVID-19 pandemic. It has a universal design for respiratory symptom monitoring and early warning and can well-equip us to be more prepared for the future respiratory-related public health crisis.

REFERENCES

- [1] M. Lipsitch, D. L. Swerdlow, and L. Finelli, "Defining the epidemiology of covid-19—studies needed," *New England journal of medicine*, vol. 382, no. 13, pp. 1194–1196, 2020.
- [2] Z. Zhang, H. Wang, C. Wang, and H. Fang, "Cluster-based epidemic control through smartphone-based body area networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 3, pp. 681–690, 2014.
- [3] W. Zhang, W. Hu, and Y. Wen, "Thermal comfort modeling for smart buildings: A fine-grained deep learning approach," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2540–2549, 2018.
- [4] H. Yang, A. Alphones, Z. Xiong, D. Niyato, J. Zhao, and K. Wu, "Artificial intelligence-enabled intelligent 6g networks," *IEEE Network*, pp. 1–9, 2020.
- [5] C. Ma, J. Li, M. Ding, H. H. Yang, F. Shu, T. Q. Quek, and H. V. Poor, "On safeguarding privacy and security in the framework of federated learning," *IEEE Network*, 2020.
- [6] A. Tak and S. Cherkaoui, "Federated edge learning: Design issues and challenges," *IEEE Network*, pp. 1–7, 2020.
- [7] Y. Luo, D. Tao, K. Ramamohanarao, C. Xu, and Y. Wen, "Tensor canonical correlation analysis for multi-view dimension reduction," *IEEE transactions on Knowledge and Data Engineering*, vol. 27, no. 11, pp. 3111–3124, 2015.
- [8] G. Laput, K. Ahuja, M. Goel, and C. Harrison, "Ubioustics: Plug-and-play acoustic activity recognition," in *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology*, 2018, pp. 213–224.
- [9] J. Laguarda, F. Hueto, and B. Subirana, "Covid-19 artificial intelligence diagnosis using only cough recordings," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 1, pp. 275–281, 2020.
- [10] S. Sun, A. A. Folarin, Y. Ranjan, and et al., "Using smartphones and wearable devices to monitor behavioral changes during covid-19," *Journal of Medical Internet Research*, vol. 22, no. 9, p. e19992, Sep 2020.
- [11] C. P. Adans-Dester, S. Bamberg, F. P. Bertacchi, B. Caulfield, K. Chappe, D. Demarchi, M. K. Erb, J. Estrada, E. E. Fabara, M. Freni et al., "Can mhealth technology help mitigate the effects of the covid-19 pandemic?" *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 1, pp. 243–248, 2020.
- [12] L. Fan, T. Li, R. Fang, R. Hristov, Y. Yuan, and D. Katabi, "Learning longterm representations for person re-identification using radio signals," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 10 699–10 709.