

Poster: SpiroMilli: Bringing Ad-hoc Spirometry to 5G Devices

Aakriti Adhikari*; Austin Hetherington*; Sanjib Sur
Computer Science and Engineering; University of South Carolina, Columbia, USA

*(Co-primary author)

{aakriti,austinth}@email.sc.edu;sur@cse.sc.edu

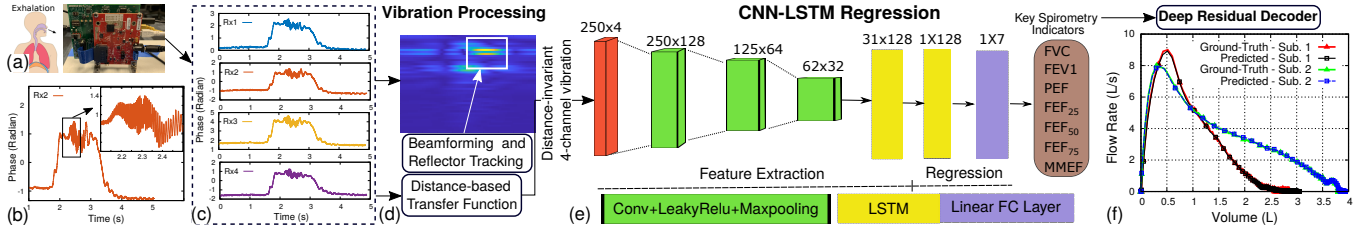


Figure 1: (a) Exhalation on a mmWave device; (b) Phase of the reflected signal shows tiny vibrations during airflow; (c) Time-synchronized vibration signals from multiple phased-array antennas; (d) Signal processing to improve fidelity, track moving reflectors, and estimate distance-invariant vibration; (e) CNN-LSTM architecture to map physical vibration to 7 key spirometry indicators; and (f) Predicted flow rate in comparison to ground-truth for two subjects.

CCS CONCEPTS

• Human-centered computing → Ubiquitous and mobile computing systems and tools; • Computing methodologies → Neural networks.

KEYWORDS

Millimeter-Wave, Spirometers, Convolutional Neural Network

ACM Reference Format:

Aakriti Adhikari*; Austin Hetherington*; Sanjib Sur. 2021. Poster: SpiroMilli: Bringing Ad-hoc Spirometry to 5G Devices . In *The 22nd International Workshop on Mobile Computing Systems and Applications (HotMobile '21)*, February 24–26, 2021, Virtual, United Kingdom. ACM, New York, NY, USA, 2 pages. <https://doi.org/10.1145/3446382.3448732>

AD-HOC SPIROMETRY MOTIVATION

The rapid evolution of the telehealth industry, accelerated recently by stay-at-home directives, has created a demand for more ubiquitous health-sensing tools. One such tool is the *Spirometer*. Spirometers have been used in traditional clinics to measure lung capacity (volume) as well as airflow (flow rate) and have wide applicability in the diagnosis of Asthma, COPD, and other pulmonary diseases. In addition, they can be used to diagnose Dyspnea, *i.e.*, shortness of breath, one of the symptoms of the COVID-19 virus. Several spirometers are available commercially for home-use, but they are either costly, cumbersome or provide limited flow information [3].

We propose *SpiroMilli*, a low-barrier means to performing spirometry at home using the millimeter-wave (mmWave) technology in 5G-and-beyond devices. To perform a test, users will hold the device in front of their mouth, fully inhale, then sharply exhale. The system will then output seven key indicators, *e.g.*, Forced Vital Capacity (FVC), Peak Expiratory Flow (PEF), *etc.*, along with a flow-volume curve (Fig. 1[f]). *SpiroMilli*'s key idea is intuitive: Strong airflow in front of the mmWave antenna creates tiny vibrations, and these vibrations affect the phase of reflected signals from nearby objects. For example, a 79 GHz device (wavelength: 3.79 mm) will register a 5 μ m displacement as a 1° phase change.

But *SpiroMilli* faces two primary challenges: (1) Phase changes should only derive from airflow vibrations, yet the sway motions of the hand and face may not allow for it; and (2) Even if the phase change is tracked accurately, a direct mapping between phase change to the seven key indicators and its corresponding flow-volume curve does not exist.

SYSTEM DESIGN

To overcome the challenges, *SpiroMilli* proposes two approaches: (1) Beamforming, reflector tracking, and distance calibrating modules which afford us with accurate phase estimation, regardless of idiosyncrasies in the users' movements; and (2) A machine-learning model that both learns and maps the vibration to key indicators and a flow-volume curve.

First, assume that the user holds the device in a static position; the phase of the reflected signals remains static. However, when airflow strikes the surface, the device starts to vibrate. Time-variant changes in the device-to-reflector distance result in phase changes of $\Delta\phi(t) = 4\pi\Delta d(t)/\lambda$, where $\Delta d(t)$ is the change in distance, and λ is the signal wavelength. Fig. 1(b) shows an example of such phase changes for a peak flow-rate of 4.67 L/s. We can remove the undesired effect of low-frequency hand sway movements on phase by applying a highpass filter. Then, combining signal beamforming and a novel reflector tracking algorithm, we ensure the source of

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

HotMobile '21, February 24–26, 2021, Virtual, United Kingdom

© 2021 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-8323-3/21/02.

<https://doi.org/10.1145/3446382.3448732>

the strongest reflections remains the same throughout the measurement. In the future, we will adopt a distance-based transfer function so phase changes can accurately predict the flow rate passing at the lips regardless of device distance.

Second, the relationship between device vibration and spirometry indicators is complex and has never been explored before. We apply a Convolutional Neural Network that learns the representative features in the vibration with LSTM to capture the temporal dependency and variations [2]. CNN-LSTM can then be used to map physical vibrations to the seven key indicators. In addition to the key indicators, clinicians also use the flow-volume curve as a diagnostic tool [3]. To this end, we have used a deep residual decoder architecture and open-source data from the CDC containing 155,000 spirometry tests [1] to learn the mapping between the key indicators and its flow-volume curve. Figs. 1(e–f) show the CNN-LSTM architecture along with the predicted flow-volume graphs

for two experimental subjects. In the future, we will evaluate our method with different device form factors, multiple subjects, and under various environmental conditions.

ACKNOWLEDGEMENT

This work was supported in part by the US National Science Foundation through NSF CNS-1910853.

REFERENCES

- [1] CDC. 2014. NHANES Comprehensive Data List. (2014). <https://wwwn.cdc.gov/nchs/nhanes/search/datapage.aspx>
- [2] Dwaipayan Biswas and Luke Everson and Muqing Liu and Madhuri Panwar and Bram-Ernst Verhoef and Shrishail Patki and Chris H. Kim and Amit Acharyya and Chris Van Hoof and Mario Konijnenburg and Nick Van Helleputte. 2019. CorNET: Deep Learning Framework for PPG-Based Heart Rate Estimation and Biometric Identification in Ambulant Environment. *IEEE Transactions on Biomedical Circuits and Systems* 13, 2 (2019).
- [3] MFI Medical. 2020. Spirometry, Oximetry and Mobile-Health. <https://www.spirometry.com/>. (2020).