Poster: Quantifying Signal Quality Using Autoencoder for Robust RF-based Respiration Monitoring

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ABSTRACT

While radio frequency (RF) based respiration monitoring for at-home health screening is receiving increasing attention, robustness remains an open challenge. In recent work, deep learning (DL) methods have been demonstrated effective in dealing with non-linear issues from multi-path interference to motion disturbance, thus improving the accuracy of RF-based respiration monitoring. However, such DL methods usually require large amounts of training data with intensive manual labeling efforts, and frequently not openly available. We propose *RF-Q* for robust RF-based respiration monitoring, using self-supervised learning with an autoencoder (AE) neural network to quantify the quality of respiratory signal based on the residual between the original and reconstructed signals. We demonstrate that, by simply quantifying the signal quality with AE for weighted estimation we can boost the end-to-end (e2e) respiration monitoring accuracy by an improvement ratio of 2.75 compared to a baseline.

CCS CONCEPTS

• Applied computing → Health informatics; **Bioinformatics**; **Health care information systems**; **• Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

Vital signs monitoring, RF sensing, signal quality assessment, signal reconstruction, unsupervised learning, autoencoder (AE)

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1 INTRODUCTION

Continuous monitoring of respiration provides rich information about common health conditions (e.g., sleep apnea and cardiac events), and is important to health status management, especially among older adults. Furthermore, a recent study showed nocturnal breathing signals to be indicative of progression of Parkinson's disease, related to degeneration in the brainstem areas that control breathing. While wearable solutions (e.g., Fitbit and Apple Watch) are popular for continuous monitoring, they require frequent charging and wearing, challenging older adults physically or cognitively, thus hard to maintain compliance. In this context, researchers have shown increased interest in device-free sensing, and demonstrated promising results with RF technologies for at-home longitudinal vital signs monitoring [3] without cooperative effort from users.

RF-based respiration monitoring works by measuring periodic variations in the received RF signals caused by the movement of the chest wall during inhaling and exhaling. However, in addition to chest wall displacements, there exist other sources in the real world scenarios that may vary and disturb RF signals in a nonlinear manner, including large body movements and multi-path reflections from cluttered environments. DL methods have been demonstrated effective in dealing with nonlinear issues for robust RF-based respiration monitoring. Nevertheless, these models typically need a substantial amount of supervised data for training, possibly only after intensive labeling efforts, and frequently such data are not openly accessible for the community.

To achieve that, we propose ***RF-Q*** [2] (see Figure 1) for **RF**-based **q**uality-aware respiration monitoring using AE, which is trained with self-supervised learning on raw respiratory signals only, free of domain expertise in providing ground truth labels or supervised information, thus easy to scale. The intuition of using the reconstruction error of AE to quantify signal quality is rooted in the observation that a trained AE tends to reconstruct signals with consistent patterns found in "regular" respiratory signals (e.g., with periodic variations in time domain and condensed energy distribution in frequency domain). In contrast, disturbed signals exhibit

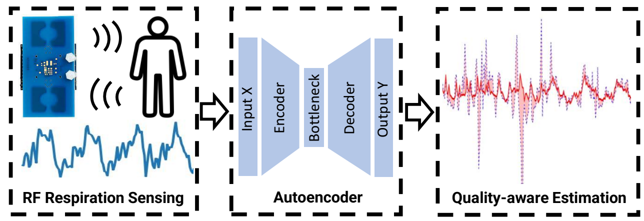

Figure 1: Overview of *RF-Q*. 1) The RF sensor measures respiration through periodic variations in the reflected RF signals, which are modulated by the movement of the chest wall during inhaling and exhaling. 2) The autoencoder (AE) neural network is optimized to reconstruct the respiratory signal of consistent patterns. 3) Therefore, the disturbed signal of unseen patterns will show large deviation from the reconstructed signal. The respiratory rate estimation is weighted on the signal quality quantified by the residual between the original and reconstructed signals to achieve improved accuracy.

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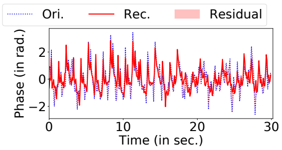
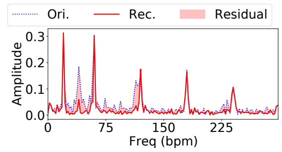
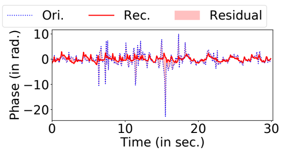


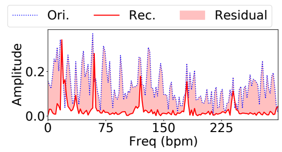
(a) Regular signal in time domain.



(b) Regular signal in frequency domain.



(c) Disturbed signal in time domain.



(d) Disturbed signal in frequency domain.

Figure 2: Examples of regular and disturbed signals in time and frequency domains. The regular signal has marginal residual between the original (Ori.) and reconstructed (Rec.) signals in both time and frequency domain. In contrast, the disturbed signal shows large residual between Ori. and Rec. signals.

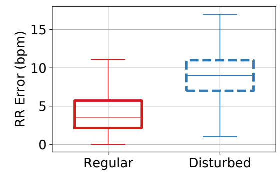
unpredictable and uncontrollable patterns that deviate significantly from the reconstructed respiratory signals of regular patterns (see Figure 2). We evaluate *RF-Q* on the RF respiratory data collected in real world testbeds, and show that the proposed *RF-Q* improves the average e2e accuracy of a baseline by a ratio of 2.75, higher than 1.94 achieved by *SQD*, a recent method.

2 *RF-Q* FRAMEWORK

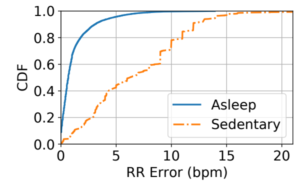
Figure 1 shows the overall framework of *RF-Q*. The key component of *RF-Q* is an autoencoder (AE) that is used to quantify the signal quality. The AE has an "hourglass" structure, comprised of an encoder, a decoder, and one bottleneck in between, which has much fewer neurons than the encoder and decoder. The bottleneck layer is optimized to learn only compressed representation about the more periodic vital signals, but ignore noises, such as jitters due to disturbance. The consistent patterns have better chance than varying patterns to be captured and learned in the bottleneck for signal reconstruction. Therefore, disturbed signals deviate significantly from their reconstructed signals, while the regular signals are close to corresponding reconstructed signals (see Figure 2). We quantify signal quality based on the residual difference, as a larger residual difference indicates a higher likelihood of signal disturbance and, therefore, poorer signal quality. We normalize the residual to a value within $[0, 1]$ as the signal quality score. For improved accuracy of respiration rate estimation, we estimate RR based on the reconstructed signal, and combine the consecutive RR estimates in a weighted sum according to respective signal quality scores.

3 EVALUATION

To evaluate *RF-Q*, we use data collected in a real-world testbed of RF-based respiration monitoring, which follows the setup of a relevant work [4]. Figure 3 shows characteristics of data collected from various settings, including during sleep and sedentary behaviors with body movements. We build two independent data sets: the first data set is of $\sim$ 40k samples for training, and the second data set of $\sim$8k samples for testing. We evaluate the performance based on the metric of respiration rate (RR) estimation error in the unit of "breaths per minute" (bpm).



(a) Box plots show RR estimation with disturbed signals has higher error than regular signals.



(b) CDF curves show RR estimation with asleep data has less errors than sedentary data because of less disturbance.

Figure 3: Data characteristics. Results show that the accuracy of RR monitoring is largely dependent on the signal quality and the awareness of signal quality is critical to robust RR monitoring.

Figure 4 shows the comparison of e2e performance between different methods. We first implement a baseline estimator based on Vital-Radio [1] to predict RR with original signals. Next, we use the baseline estimator to predict RR with reconstructed signals from the trained autoencoder. Then, in *RF-Q*, the estimated RRs from the reconstructed signals are combined with the corresponding signal quality scores for weighted estimation. In addition, we compare the performance with *SQD* [4], a supervised method for signal quality detection. When we compare the average accuracy of each method to the baseline with original signals, we find that *RF-Q* achieves an improvement ratio of 2.75, higher than 1.38 achieved by RR estimation with reconstructed signals, and 1.94 achieved by *SQD*.

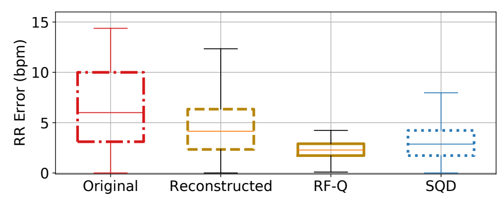


Figure 4: Original signals (including both regular and disturbed ones) result in a median RR error of 6.7 bpm with a baseline RR estimator. The reconstructed signals from the trained autoencoder have a reduced median RR error (4.6 bpm). The RF-Q further reduces median RR error to 2.4 bpm. The SQD detects and excludes the disturbed signals from the original signals and achieves a reduced median RR error (3.2 bpm).

4 CONCLUSION AND FUTURE WORK

In this work, we present *RF-Q* that uses an autoencoder neural network to quantify the signal quality for quality-aware and robust RF respiratory monitoring. Experiments show that our proposed *RF-Q* significantly improve the average accuracy of RR estimation from a baseline estimator by a gain ratio of 2.75, which is higher than a gain ratio of 1.94 achieved by a supervised method *SQD*. In the future, we plan to study and compare *RF-Q* with different variants of AE. Furthermore, we plan to deploy *RF-Q* at the edge for online health monitoring and analytics in real homes.

REFERENCES

[1] Fadel Adib, Hongzi Mao, Zachary Kabelac, Dina Katabi, and Robert C Miller. 2015. Smart homes that monitor breathing and heart rate. In *ACM CHI'15*. 837–846.
[2] Zongxing Xie, Ava Nederlander, Isac Park, and Fan Ye. 2023. RF-Q: Un-supervised Signal Quality Assessment for Robust RF-based Respiration Monitoring. In *CHASE'23*.
[3] Zongxing Xie, Bing Zhou, Xi Cheng, Elinor Schoenfeld, and Fan Ye. 2022. Passive and Context-Aware In-Home Vital Signs Monitoring Using Co-Located UWB-Depth Sensor Fusion. *ACM Transactions on Computing for Healthcare* 3, 4 (2022).
[4] Zongxing Xie, Bing Zhou, and Fan Ye. 2021. Signal quality detection towards practical non-touch vital sign monitoring. In *ACM BCB'21*. 1–9.