

RF-Q: Unsupervised Signal Quality Assessment for Robust RF-based Respiration Monitoring

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ABSTRACT

Continuous monitoring of respiration provides invaluable insights about health status management (e.g., the progression or recovery of diseases). Recent advancements in radio frequency (RF) technologies show promise for continuous respiration monitoring by virtue of their non-invasive nature, and preferred over wearable solutions that require frequent charging and continuous wearing. However, RF signals are susceptible to large body movements, which are inevitable in real life, challenging the robustness of respiration monitoring. While many existing methods have been proposed to achieve robust RF-based respiration monitoring, their reliance on supervised data limits their potential for broad applicability. In this context, we propose, *RF-Q*, an unsupervised/self-supervised model to achieve signal quality assessment and quality-aware estimation for robust RF-based respiration monitoring. *RF-Q* uses the reconstruction error of an autoencoder (AE) neural network to quantify the quality of respiratory information in RF signals without the need for data labeling. With the combination of the quantified signal quality and reconstructed signal in a weighted fusion, we are able to achieve improved robustness of RF respiration monitoring. We demonstrate that, instead of applying sophisticated models devised with respective expertise using a considerable amount of labeled data, by just quantifying the signal quality in an unsupervised manner we can significantly boost the average end-to-end (e2e) respiratory rate estimation accuracy of a baseline by an improvement ratio of 2.75, higher than the gain of 1.94 achieved by a supervised baseline method that excludes distorted data.

CCS CONCEPTS

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

KEYWORDS

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

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1 INTRODUCTION

The respiratory rate, one of the basic vital signs, is an important bio-indicator typically measured at clinical visits for health status assessment [2, 3]. Recently, researchers show that the analysis of continuous respiration trends is effective in monitoring the progression or recovery of diseases (e.g., post-COVID conditions). For example, a novel phenotyping of COVID recovery has been identified using long-term trajectories of respiratory symptoms [21]. Moreover, researchers have demonstrated correlations between Parkinson's disease and nocturnal breathing signals using an artificial intelligence (AI) model [20]. Despite their popularity, wearable solutions (e.g., Apple Watch) require frequent charging and wearing, making it difficult to maintain compliance, especially among those who may feel physically or cognitively challenged with smart devices. As an alternative, radio frequency (RF) technologies achieve passive vital signs monitoring [15, 18], and require no human cooperative effort and show promise for long-term, in-home monitoring [16, 20].

The intuition of RF-based respiration monitoring is that the chest wall displacements due to respiration cause periodic variations in the RF signals, from which the respiration information can be extracted [1, 13]. While RF sensing has been demonstrated to be promising for continuous respiration monitoring, its robustness remains an open challenge [14]. To be specific, inadvertent body movements cause large disturbances in RF signals, and multi-path reflections from the cluttered environment and the intermodulation between respiration and heartbeat due to non-linear effects further challenges RF-based respiration monitoring. To address the above issues, solutions are proposed in the three categories as follows: i) detecting and excluding the motion-disturbed RF signals to avoid erroneous respiration extraction [1, 17]; ii) reconstructing respiration signals in the presence of motion disturbance based on deep learning methods [19, 22]; iii) formulating continuous respiration monitoring as a tracking problem to smooth out disturbed readings according to the temporal continuity of the vital signs [8, 15]. While we have seen promising results reported with such approaches mostly in well controlled lab environments, we have yet seen them handily applied in real homes and at scale. One reason is that they usually require domain expertise to train customized models that require a large amount of labeled data, which is prohibitively costly. Furthermore, the development (e.g., design or training) of a model

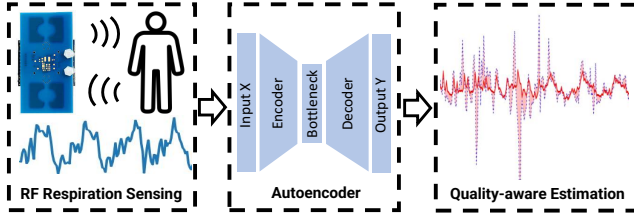


Figure 1: Overview of *RF-Q*. 1) The respiration-induced chest wall displacement causes periodic variations in RF signals repeatedly emitted and received by the RF sensor. 2) The autoencoder (AE) model is optimized to reconstruct the input signal. Because the trained autoencoder tends to reconstruct signals of consistent patterns, the output will show large deviation from the input if it has strong disturbances of dynamic and unseen patterns. 3) The residual between the reconstructed and original signals is used to quantify the signal quality, based on which a weighted fusion is applied to achieve reliable respiratory rate estimation.

for RF-based respiration monitoring may be prone to the bias of researchers or data, thus hard to generalize.

To achieve a robust *RF*-based respiration monitoring solution without labeling efforts, we propose *RF-Q* (illustrated in Figure 1) for quality-aware respiratory rate estimation based on an unsupervised signal quality assessment that provides contextual information about how reliable the respiratory information can be extracted from noisy RF signals without ground truth. To be specific, we apply a self-supervised learning framework to train an autoencoder (AE) model, of which the decoder is optimized to reconstruct the original signal from a latent representation compressed by the encoder. We use the reconstruction error, the residual between the reconstructed signal and original input, as the indicator of the signal quality. This is inspired by the fact that RF vital signal observations available for vital signs extraction are of consistent patterns (e.g., condensed energy distribution in frequency domain, periodic variations in time domain). However, the disturbed signals are of varying patterns, which are uncontrollable and nonrecurring, thus unseen to the training dataset, and the trained AE model would have great difficulty in faithful reconstruction. Therefore, we use the reconstruction error to quantify the signal quality. As Figure 2 shows, a larger reconstruction error indicates a larger deviation from regular patterns, attributed to the signal quality with disturbance.

In addition, we make full use of an AE to reconstruct the disturbed portion of RF respiratory signals combined with signal quality assessment in a weighted fusion for improved e2e performance of RF respiration monitoring. To evaluate the proposed *RF-Q*, we conduct experiments of RF respiration monitoring using real-world testbeds in interference-rich environments. We show *RF-Q* is discriminative of signal quality between the regular and disturbed ones. By combining the signal quality score and the reconstructed signal in a weighted fusion, *RF-Q* boosts the end-to-end (e2e) respiration accuracy of a baseline estimator by an improvement ratio of 2.75. We also conduct experiments to study the impact of the ratio between the regular and disturbed signals on training the AE model, and show that the difference is marginal for the ratio within the range of 10 to 90 percent. This observation implies that the training itself does not require much labeling effort to differentiate between regular and disturbed signals, which is time consuming and effort intensive.

We summarize our key contributions as follows:

- We propose, *RF-Q*, an unsupervised signal quality assessment method for robust RF-based respiration monitoring using an AE, which can be trained by using only input data with very little effort or domain expertise in providing labels or ground truth, thus easy to scale.
- We evaluate *RF-Q* with RF respiratory data collected in real world testbeds. We show that the proposed *RF-Q* can boost a baseline by an improvement ratio of 2.75 in average e2e respiration monitoring accuracy with a weighted fusion of the signal quality scores and reconstructed signals. Such performance is achieved on all data, even better than what achieved by *SQD* on excluding data of bad quality.

2 BACKGROUND AND RELATED WORK

The RF signal have been thoroughly investigated as a sensing modality for vital signs extraction throughout the last few decades [1]. The fundamental idea is that chest movement from breathing and rhythmic heartbeats modulates reflected RF signals, which may be analyzed through phase [5, 7], or derived Doppler features [4, 9]. The majority of currently available RF vital sign detection systems were tested in controlled environments with a human subject who remains still in front of the radar. However, in real-world situations, the person could do more complex activities [16] that severely disturb vital signals and impair physiological parameter estimation, challenging robustness of RF-based vital signs monitoring. To eliminate destructive effect of motion artifacts on RF-based vital signs monitoring, many methods have been proposed to either recovery the signals in the presence of motion disturbance [19, 22], or exclude the motion-disturbed RF signals for reliable vital signs estimation [1, 17]. However, they all used supervised learning techniques from labeled data, which is often time-consuming and expensive, limiting their potential for broad applicability. Inspired by the related work using unsupervised learning for ECG signal quality assessment[12], we apply a self-supervised/unsupervised learning scheme to train an autoencoder model for quality-aware vital sign monitoring.

3 RF-Q FRAMEWORK

Figure 1 shows an overview of *RF-Q* which has three components: RF respiration sensing, signal quality assessment with autoencoder and quality-aware estimation.

3.1 RF Respiration Sensing

The RF signals propagated in the monitoring space carry information about dynamics of human subjects, including the chest wall displacements due to inhaling and exhaling. The respiratory information can be extracted from the baseband of the received RF signals, which can be modeled as:

$$s(t) = \alpha_d e^{-j \frac{4\pi f_c}{c} d(t) + \theta} + \omega, \quad (1)$$

where α_d denotes the magnitude of the received signal depending on the distance and radar cross-section (RCS) of the target. f_c denotes the center frequency of RF signals, and c is the propagation speed of RF signals, i.e., the speed of light. θ denotes an initial phase, and ω denotes the measurement noise. The information about respiration-induced chest wall displacements $d(t)$ can be

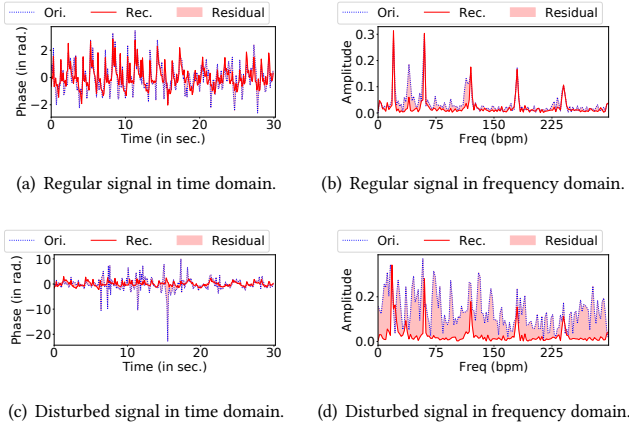


Figure 2: Examples of regular and disturbed signals in time and frequency domains. The reconstructed signal (Rec.) of the regular signal matches the original signal (Ori.), and the residual between them is limited in both (a) time and (b) frequency domains. The disturbed signal has (c) large jumps in the time domain and (d) its spectrum is noisy. However, only more regular variations with a condensed spectrum can be reconstructed, thus the residual between the original and reconstructed ones is large.

demodulated from the phase of the baseband signal $s(t)$. While the received RF signals carry information of respiration, they are often noisy, interfered and disturbed by various sources, and thus reliable respiration extraction is difficult. Awareness of the signal quality is critical to robust long-term respiration monitoring.

3.2 Autoencoder for Signal Quality Assessment

We achieve unsupervised signal quality assessment with an autoencoder (AE) network. The goal of an AE is to generate an output that reconstructs the input to the maximum extent. The AE has an “hourglass” structure, comprised of an encoder, a decoder, and one bottleneck in between that is made up of much fewer neurons. This structure allows the bottleneck to capture only the most representative features of the original input data and ignore the detailed specifics of the input data, such as outliers, in order to reconstruct the input as closely as possible. Therefore, it is much easier to reconstruct regular signals of consistent patterns than disturbed signals of dynamic patterns. We leverage this observation, and use the residual difference between the reconstructed and original signals to quantify the signal quality. The larger the residual difference, the more likely that the corresponding input signal is disturbed. We model the residual difference with the mean squared error (MSE) between the input (X) and output (Y), which is also used as the loss function $\mathcal{L}$ to optimize AE:

$$\mathcal{L} = \text{MSE}(X, Y) = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2, \quad (2)$$

where x_i and y_i are samples in input and output signals, respectively. Because the AE is trained using only input signals and their reconstructed version without supervised information (i.e., labels or ground truth), this method is self-supervised, which is a variant of unsupervised method.

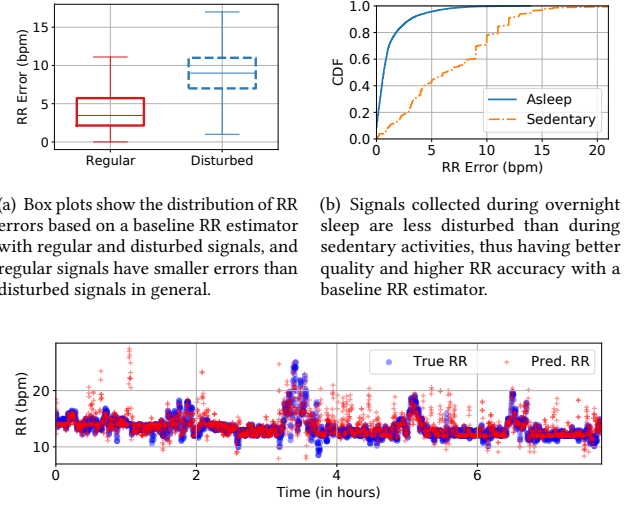


Figure 3: Data characteristics. Results show that the accuracy of RR monitoring is largely dependent on the signal quality and the awareness of signal quality is critical to robust RR monitoring.

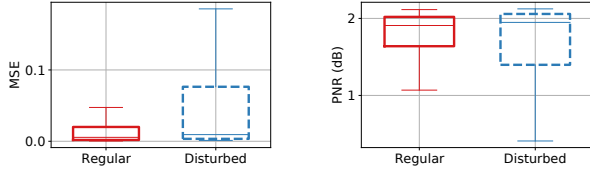
3.3 Quality-aware Estimation

With the AE trained with unsupervised data for signal quality assessment, we can combine the quantified signal quality and the reconstructed signal from AE for better estimation accuracy. The idea is that we assign a larger weight to a signal with a better signal quality for respiration rate estimation, and mitigate the detrimental impact of disturbed signals with a small weight. By doing so we can fuse the information for reliable respiratory rate estimation from local periods, during which the variability of vital signs (e.g., respiratory and heart rates) is limited. To formally describe it, we denote the original signal by X_i as input to AE, its reconstructed signal from AE by $\mathcal{G}(AE(X_i))$, $\mathcal{G}$ as a respiratory rate estimator (see §4.2 for detailed implementation), and $\hat{r}_i$ is one estimation of the local ground truth rr , and we use the reconstructed signal for respiratory rate estimation: $\hat{r}_i = \mathcal{G}(AE(X_i))$. Two requirements are considered defining a signal quality score (Q) as the weight: 1) a larger weight indicates a better signal quality, that is, with a smaller residual difference $\mathcal{D}(X_i) = \text{MSE}(X, AE(X_i))$, 2) the weight is normalized with (0, 1) given unbounded residual. We empirically define a signal quality score (Q) in the form of exponential decay, as $Q_i = e^{-\lambda \cdot \mathcal{D}(X_i)}$. The fused respiratory rate estimation $\hat{r}$ is expressed as a weighted summation:

$$\hat{r} = \frac{\sum_{i=1}^N (Q_i \cdot \hat{r}_i)}{\sum_{i=1}^N Q_i}, \quad (3)$$

4 EVALUATION

In this section, we first describe the data collection and datasets, and then introduce the metrics and baselines. Lastly, we discuss the experimental results and summarize findings.



(a) Distribution of MSE of regular and disturbed signals. (b) Distribution of PNR of regular and disturbed signals.

Figure 4: Box plots show that two classes of signals are more separable in the dimension of MSE than PNR.

4.1 Data Collection and Datasets

To evaluate *RF-Q* and validate our hypothesis, we conduct experiments with data collected in the real-world testbed for RF-based respiration monitoring from 8 participants, whose heights ranged from 156–192 cm and weights ranged from 49–108 kg. The RF data collection testbed is implemented with a COTS IR-UWB sensor XeThru X4 [11], of which the frequency band is 7.25–10.2 GHz. The RF sensor is configured to repeatedly transmit impulse radio signals and measure the displacements of target chest wall at 10 Hz. We use a 30-seconds time window to extract respiratory information, so the input is a 1-D time series data of the length 300. We obtain the ground truth of continuous respiratory rates from a FDA approved medical device, Masimo Pulse Oximeter [10].

We collected data in various settings, including during sleeping and sedentary behaviors with frequent body movements as well as lab controlled settings, where participants were instructed to keep stationary. The data is balanced across 8 participants. We build two data sets, independent to each other. The first data set has in total $\sim 40k$ samples for training, and the second data set has in total $\sim 8k$ samples for testing, and each sample is a time series vector of a length 300 in a 30-second time window. Although the unsupervised training requires no labels, we manually label data into two classes for better understandings of data characteristics. One class is of “regular” patterns, e.g., periodic variations in time domain (Figure 2(a)) and condensed energy distribution in frequency domain (Figure 2(b)). The other class is of dynamic patterns, e.g., large jumps in time series (Figure 2(c)) and noisy spectrum (Figure 2(d)). Figure 3(a) show the distribution of respiration rate errors between two classes. Notably, data collected during sedentary behaviors (i.e., reading, surfing the internet and typing) include more disturbed signals thus worse resulting RR accuracy than data collected during sleep (Figure 3(b)). In contrast, data collected during sleep include more regular signals, and the resulting respiratory rate (RR) estimation is more accurate and aligned with the ground truth (shown in Figure 3(c)). In the default setting, we use comparable amounts of “regular” signals and disturbed signals for training, and we will also study the impact of the ratio between “regular” and disturbed data.

4.2 Metrics and Baselines

For the robustness of respiration monitoring, we evaluate the end-to-end performance in the metric of respiratory rate estimation error compared to the ground truth, expressed as $e_{RR} = |\hat{r} - r|$ in the unit of breaths per minute (bpm).

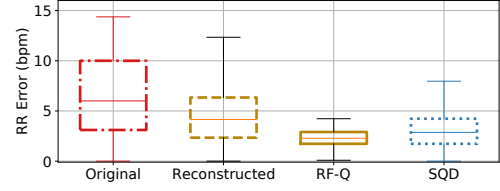


Figure 5: Original signals (including regular and disturbed ones) result in a 75-percentile RR error of 10.0 bpm with a baseline RR estimator. The reconstructed signals from the trained autoencoder have a reduced 75-percentile RR error (6.5 bpm). The RF-Q combines the reconstructed signals and the signal quality scores for a further reduced 75-percentile RR error (2.8 bpm). The SQD detects and excludes the disturbed signals from the original signals and achieves a reduced 75-percentile RR error (4.2 bpm).

Autoencoder neural network. The autoencoder of *RF-Q* has an “hourglass” structure with one encoder and one decoder symmetric to each other. The encoder takes the 1D input tensor in the dimension of (1, 300), and it has two fully-connected (fc) layers, one with 100 neurons and the other with 40 neurons, each is followed by an ReLu activation layer. Between the encoder and decoder, the bottleneck has 10 neurons. The decoder is structured in a reverse order to the encoder. We use Adam as the optimizer to train the model. We use the trained autoencoder to reconstruct input signals, and we use MSE to quantify the deviation between the input and output signals thus the signal quality.

RF respiration monitoring. We use an existing respiratory rate estimation algorithm proposed in *Vital-Radio* [1] as a baseline, because it is effective with a light and explainable implementation. It shows reasonable performance given regular signals. For example, its predicted RR matches the ground truth of RR during sleep for most of the monitoring period during sleep as shown in Figure 3(c). We also follow *Vital-Radio* [1] to use the peak-to-noise ratio (PNR) as a baseline of signal quality indicator, which models the sharpness of the spectrum due the periodic variations. In addition, we use signal quality detector (SQD) [17] as another baseline of signal quality indicator, which classifies the availability of RF signals for reliable vital signs extraction.

4.3 Experimental Results

4.3.1 Signal quality indicator. we compare the effectiveness between MSE and PNR, based on separability and correlations with the target metric, which is e2e RR accuracy in this paper. Figure 4 show that two classes are less overlapped thus more separable using the metric of MSE compared to PNR.

4.3.2 End-to-end respiratory rate monitoring. Figure 5 shows the comparison of e2e RR accuracy between different methods. We first use *Vital-Radio* [1] as the baseline to estimate RR with original signals, and then estimate RR with reconstructed signals from the trained autoencoder. *RF-Q* combines the reconstructed signals with the corresponding signal quality scores for better estimation with weighted summation. Besides, we compare the performance with SQD [17], which detects and excludes the corrupted signals to avoid erroneous estimation. SQD achieves better e2e accuracy than using only reconstructed signals, however, at the cost of a portion (more than 30%) of partially disturbed signals that could have been salvaged to have reasonable estimation. In addition to comparison

Table 1: Comparison of gain according to the improvement ratio of average accuracy (Avg. Acc.) compared to the baseline.

Method	Avg. Acc. (bpm)	Gain
Original	6.39	1
Reconstruction	4.64	1.38
RF-Q	2.32	2.75
SQD	3.29	1.94

of the distribution of RR errors, we show the gain of each method according to the improvement ratio of average accuracy compared to the baseline with original signals in Table 1. *RF-Q* largely boosts the accuracy of the baseline by the improvement ratio of 2.75.

4.3.3 Impact of ratio between “regular” and disturbed signals. In real life, we have no control on the ratio between “regular” and disturbed signals for training the autoencoder neural network (AE). We evaluate the model trained with different ratios (including 10:90, 30:70, 50:50, 70:30, and 90:10). Interestingly, no significant difference has been observed between all settings, while a larger percentage of the training data being “regular” signals shows a marginal increase in the e2e gain. This implies that AE can learn effective representation for reconstructing signals with regular patterns given sufficient training data. Besides, the nocturnal respiratory data consistently have a high percentage of regular signals, and can be used for training AE in *RF-Q*.

5 DISCUSSION

Based on results from this preliminary study, we certainly see there is room for further improvement. Nonetheless, it demonstrates that self-supervised learning with a vanilla autoencoder for signal quality assessment without extra supervised information can largely boost the accuracy of respiration monitoring. With that, we believe it would also be interesting to see how this method would perform with other RF technologies, e.g., WiFi and RFID in related work, even though there are no such benchmarks for direct comparison. As a preliminary study, *RF-Q* leaves a few directions to further studies. First, we only explore one simple autoencoder architecture with one single configuration of hyper-parameters. In the future, we will investigate different autoencoder variants, e.g., variational autoencoder [6], with more diverse configurations of hyper-parameters. Second, we are yet to demonstrate its effectiveness with sophisticated vital sign estimators rather than a simple baseline estimator. We will also evaluate the effectiveness of *RF-Q* for heartbeat extraction. Finally, we will conduct more experiments to understand the impact of the amount and type of training data, e.g., with different levels of body movements, on the performances.

6 CONCLUSIONS

In this paper, we present, *RF-Q* for quality-aware and robust RF respiratory monitoring. We propose to use an autoencoder neural network for quantifying the signal quality and reconstructing regular signals of consistent patterns in an unsupervised scheme. Experiments show that our proposed *RF-Q* largely reduce the average error of RR estimation from a baseline estimator by a gain of 2.75, which is higher than a gain of 1.94 achieved by a supervised method *SQD* that detects and excludes data of bad quality.

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