



Random forest classification of breathing phases from audio signals recorded using mobile devices

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Abstract

Respiration rate (RR) and other respiratory features, such as inhale-to-exhale ratio (IER) and duration of breathing phases can be used as marker of respiratory and lung conditions and to modulate autonomic function in biofeedback applications. In this study, audio respiration signals were recorded by 112 participants using smartphones. RR was estimated using a frequency-domain method. Acoustic features were extracted from the audio signals and random forest was used to classify inhales, exhales and respiratory pauses, with ROC AUCs of 0.84 and 0.95 for inhales and exhales respectively. RR was estimated with a mean absolute error (MAE) of 0.63 bpm. IER was estimated with a MAE of 0.37, with 76% of the dataset reporting a MAE of less than 0.20. The results demonstrate a computationally efficient approach to estimate respiratory features from audio signals recorded using smartphones that can be easily implemented in real-time for large-scale home monitoring or biofeedback applications.

Index Terms: respiratory rate, inhale-to-exhale ratio, acoustic features, random forest, classification.

1. Introduction

Respiratory rate is a vital sign used as marker of many respiratory, lung and heart conditions [1]–[3]. It can be used for early detection of cardiopulmonary arrest [1], [2] and has been used as part of a composite Patient-at-Risk score to identify in-patients that need to be, or would benefit from being, transferred to the intensive care unit [3]. Respiratory variables beyond respiratory rate can also be markers of various conditions and can be used to provide respiratory feedback to modulate autonomic function [4]. The ratio of inhalation time to exhalation time is associated with heart rate variability in adults [5]–[7] has been used to detect stress [8], anxiety [8], [9], and even as a feature for identity authentication since it can be a marker for sedentary breathing patterns [10]. Furthermore, inhalation time as a fraction of the total respiratory period is associated with airway obstruction [11], [12].

The COVID-19 pandemic has emphasized the need for remote monitoring of health that can be easily deployed into homes with technology already available to the general public. Breathing sounds can be recorded using smartphone-embedded microphones without the need for medical training, providing an option for low-cost remote health monitoring of a large group of patients. Previous studies have presented methods to estimate respiratory rate using audio data [13], [14] based on frequency-domain methods, together with signal processing techniques. Other studies have applied classification methods

to audio data to identify periods of inhalation, exhalation and respiratory pauses [15], [16]. Detection of inhale in breathing sounds can be challenging, however, due to the lower amplitude of the inhale signal when compared to exhales events and their similar acoustic characteristics.

In this study, we present a new approach to classify pause, inhalation and exhalation periods in acoustic respiration signals recorded using smartphones. Respiratory rate is estimated along with inhalation and exhalation durations, and inhale-to-exhale ratio (IER). A random forest classifier is used to distinguish between pauses, inhales and exhales using acoustic features and post-processing of the classifier probabilities. The estimated RR and IER are compared with the same metrics extracted from annotated signals in 112 participants.

2. Materials and Methods

2.1. Dataset

The dataset consisted of audio signals recorded by 112 participants (aged 41.74 ± 13.53 , 70 female) during quiet breathing with their phone held horizontally at a distance of 2 cm from their mouth/nose, Figure 1. The data were a subset of a larger data set recorded remotely where the inclusion criteria for the present study required that inhalation was audible or visible in the signal when examined during manual annotation of the data. The study was approved by the UCD Human Research Ethics Committee and St. Vincent’s Hospital Ethics Committee. Full details of the experimental protocol are provided in [13].

2.2. Data annotation

Audio data were annotated by two independent researchers and breathing phases labeled as ‘Inhale’ and ‘Exhale’. A third researcher reviewed the annotations and settled any mismatches between the two first annotations for each signal. A third category ‘Pause’ was created for the parts of the signal which were not annotated as either ‘Inhale’ or ‘Exhale’. Pauses can also be present in breathing and are characterized as the cessation of the airflow [17], thus the labels used better reflect the breathing process.

2.3. Respiratory rate estimation

Respiratory rate was estimated from the fundamental frequency of the envelope of the acoustic respiration signal. Audio signals were low pass filtered with a cut-off frequency of 3.8 kHz with a 4th order Butterworth filter applied forwards and backwards.

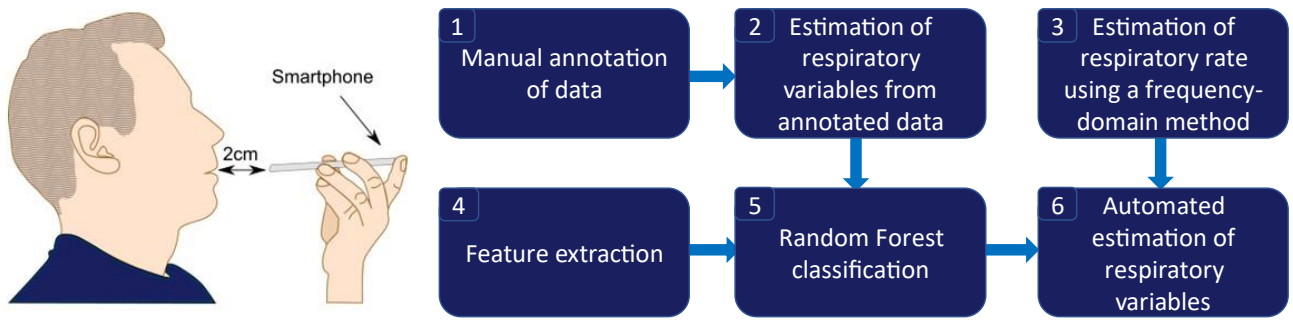


Figure 1: Data collection set-up for recording of breathing with mobile devices.

The cutoff frequency of 3.8 kHz was chosen to accommodate signals recorded with a sampling frequency of 8 kHz. The mean value of the signal was subtracted prior to full wave rectification. The signal envelope was then estimated by applying low-pass 2nd order Butterworth filter was applied to the rectified signal. The envelope was transformed to the frequency domain using Welch's method, with a window length of half the signal length, nfft of twice its length and overlap of 50%. The frequency at which the highest peak in the power spectrum occurred within the 0.09 Hz and 1 Hz frequency band, corresponding to respiratory rates in the range 5-60 bpm, was identified and scaled to estimate the respiratory rate in breaths per minute.

2.4. Feature extraction

Forty features were estimated using a custom developed scripts in Python. Each audio signal was divided into epochs of 0.1 s with 0.5 overlap. Features were estimated for each epoch separately. The following features were selected from acoustic voice features commonly used in voice and speech analysis [18]–[20]: median frequency (F0), its standard deviation (SD F0), harmonics-to-noise ratio (HNR), jitter, relative average perturbation of jitter (RAP), five-point perturbation quotient (PPQ5), difference of differences in periods (DDP), glottal-to-noise excitation rate (GNE). Cepstral-based features from the Mel frequency cepstral coefficients (MFCC) were also estimated [21], with the mean and standard deviation of the mean of the 13 MFCCs (mean MFCC, SD MFCC), the standard deviation of the Delta of the calculated MFCCs (mean Delta, SD Delta) and the second order delta of the MFCCs (mean Delta 2, SD Delta 2). Spectrum-based features, such as the maximum power in the power spectrum (maxPower), the frequency in which the maximum power occurs (freqMaxPower), the median frequency (medianFreq) and the spectral edge were estimated. Finally, a number of features related with the amplitude of the signal were estimated, including the mean, standard deviation (SD), median, integral, 5th and 95th percentiles, kurtosis and skewness of the rectified signal, along with the integral of the signal after the Teager-Kaiser Energy Operator (TKEO) [22]. The normalized values of F0 (normF0) and maxPower (normMaxPower) were included to account for individual differences. To account for the change from epoch to epoch by differentiating one epoch with respect of the next. This was done for F0, SD MFCC, SD Delta, SD Delta 2, spE, mean, SD, median, sum, 5th and 95th percentiles, kurtosis, skewness and TKEO: diff_F0, diff_meanMFCC, diff_meanDelta, diff_meanDelta2, diff_SDMFCC, diff_SDDelta, diff_SDDelta 2, diff_spE, diffMean, diffSD, diffMedian, diffSum, diff_5prctl, diff_95prctl, diffKurtosis, diffSkewness, diffTKEO.

2.5. Machine learning model

To reduce the number of features considered by the machine learning model, correlation analysis was performed on the feature matrix. Spearman rho was used as not all features were normally distributed. Features that were highly correlated with other features ($\rho > 0.8$) were removed, resulting in 21 features being retained.

A Random Forest classifier was implemented to classify each epoch as inhale, exhale, or pause. A Decision Tree was also implemented to compare performances with the Random Forest. However, the Random Forest algorithm was selected since it is a versatile model that is efficient, is suitable for multiclass classification and yields an interpretable model for this type of healthcare application. A nested grid search was performed to optimize the hyperparameters (maximum depth, minimum samples split, ccp alpha and the maximum samples) of the random forest model. Nested feature selection within the cross-validation was then performed using a backwards sequential search wrapper and specifying 10 features as the maximum to be included. The relative feature importances were analysed, Figure 2.

Ten-fold cross-validation with nested processes was performed. All epochs for a certain participant were contained within one and only one fold. For each fold, we performed undersampling of the majority class to avoid unbalanced datasets. Each epoch was classified as the class (pause/inhale/exhale) with the highest probability, as determined by the random forest model.

Performance metrics were calculated as the mean across all cross-validation folds: precision, recall, F1-score and the area under the receiver operating characteristic (AUC ROC) were estimated for each respiratory class, along with the overall three-class accuracy. Following cross-validation, feature selection and model development were performed using the entire dataset to develop the final model.

2.6. Post-processing

The thresholds for the classification classes were adjusted based on the ROC curves for each breathing phase to bias the post-processing to the inhale class to reduce the misclassification of the inhale epochs. The quantity and length of each respiration phase was estimated from the epochs classified by the Random Forest model. If an unphysiological inhale duration of less than 3 epochs was detected, the probabilities for the inhale class were examined and every epoch lying between two adjacent inhale phases with probability greater than 0.3 was re-labeled as an 'inhale' epoch. A similar process was applied to exhale epochs if exhale duration less than 3 epochs was identified.

To reduce the influence of misclassification of spurious epochs a median filtered with a kernel with a length of 11 points was applied to signals containing more than 60 inhales or exhales in 90 s. If the ratio of the number of inhales to the number of exhales was greater than 1.5, indicating that the exhale class was occurring 50% more frequently than the inhales, the same median filter was also applied.

The mean inter-breath interval (IBI) for each audio signal was extracted from the previously estimated respiratory rate. The distance between breathing phases (DBP) was estimated for inhales, exhales and pauses. A series of conditions was applied to improve classification performance. First, if the DBP for pauses was greater than the mean IBI for that participant, the threshold for inhales was decreased to 0.25 to search for a missing inhale. If the DBP for the inhale class was greater than $1.5 \cdot \text{IBI}$, the threshold for inhales was decreased to 0.3 to identify missing inhales. Similar conditions were then applied to the exhales class. To account for short breathing events that may have been missed by the median filter, the DBP for inhales and exhales were reexamined, and if either was less than $0.3 \cdot \text{IBI}$, their probabilities were analysed and their threshold decreased to 0.3. Lastly, to account for improperly grouped breathing events, the classification threshold for inhales or exhales was decreased again to 0.3 if the DBP of inhales and exhales was bigger than $1.5 \cdot \text{IBI}$.

2.7. Breathing events metrics

The mean inhale and exhale duration was estimated for each recording along with the ratio of inhale to exhale duration (IER) and compared to the values from the annotated signals. As the number of detected inhales and exhales were not always equal, IER was estimated using the minimum of the number of detected inhales and number of detected exhales. To avoid edge errors when calculating IER at the start and end of the recordings, only the events in the middle of the recorded were included in the IER calculation.

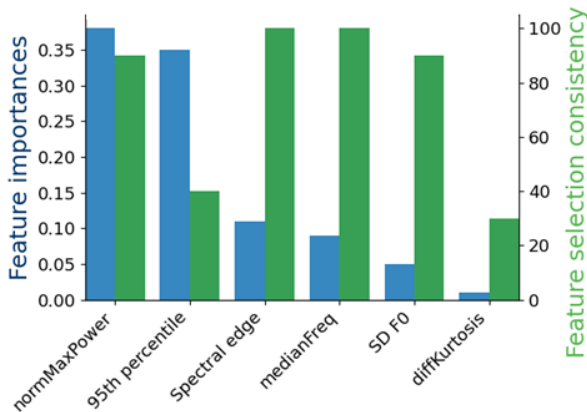


Figure 2: Feature importance for the final model and feature consistency during nested feature selection within the 10-fold cross-validation.

3. Results

3.1. Machine learning model

The grid-search hyperparameter optimization within the 10-fold cross-validation resulted in the minimum samples split parameter always being selected as 0.1, ccp alpha as 0 and maximum samples for splitting the tree as 0.6. The maximum

depth of the nodes was selected as 3 for 1 fold, 4 for 3 folds and 5 for 6 folds. For the nested feature selection, medianFreq and spectral edge were selected in all 10 folds.

The final set of features selected by the model were normMaxPower, medianFreq, spectral edge, SD F0, diffKurtosis and the 95th percentile. The relative importance of each feature along with their selection consistency during cross-validation is presented in Figure 2.

Performance metrics for Random Forest classification of each respiratory event are presented in Table 1, and the receiver operating characteristics for each class in Figure 3. The overall balanced accuracy, precision, recall and F1-score for the model were all 73.0%. The pause threshold was set to 0.42, inhale to 0.38 and exhale to 0.427. In contrast, the Decision Trees model tested as comparison yielded an accuracy of 69.7% and an AUC ROC curve for inhale and exhale were 0.80 and 0.92.

Table 1: Performance metrics for each respiratory class.

	Inhale	Exhale	Pause
Precision	59.5%	78.8%	73.9%
Recall	57.6%	87.5%	67.9%
F1-score	58.5%	83.0%	70.8%
ROC AUC	0.84	0.95	0.55

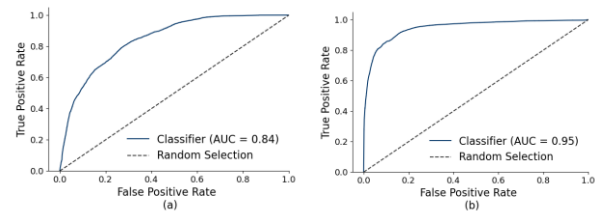


Figure 3: ROC curves for classification of (a) inhale and (b) exhale.

3.2. Respiratory rate and inhale-to-exhale ratio

A sample audio recording, with post-processed classifier results, is presented in Figure 4. The mean absolute error (MAE) of the respiratory rate averaged over all participants was 0.63 breaths per minute (bpm) with a standard deviation of 1.04 bpm and a mean absolute percentage error (MAPE) of 4.6%. The annotations for RR revealed a group mean of 13.74 ± 4.45 bpm while the algorithm reported a group mean of 13.56 ± 4.50 bpm. The IER MAE was 0.37 with a standard deviation of 0.43 for all 112 signals analyzed, Table 2.

The MAE of the respiratory rate was lower than 0.5 bpm for 76% of the signals analysed. These signals had a IER MAE of 0.20. The remaining 24% of the dataset were found to have substantially higher IER MAE of 0.88, consistent with the classifier metrics of 73% accuracy across all classes.

Table 2: Mean, standard deviation and mean absolute error for breathing events.

Measurement	Dataset	Mean \pm SD	MAE
Inhale duration (s)	Annotated	1.22 ± 0.39	0.56
	Predicted	1.19 ± 0.98	
Exhale duration (s)	Annotated	1.72 ± 0.60	0.38
	Predicted	1.69 ± 0.88	
Inhale-to-exhale ratio	Annotated	0.75 ± 0.20	0.37
	Predicted	0.76 ± 0.61	

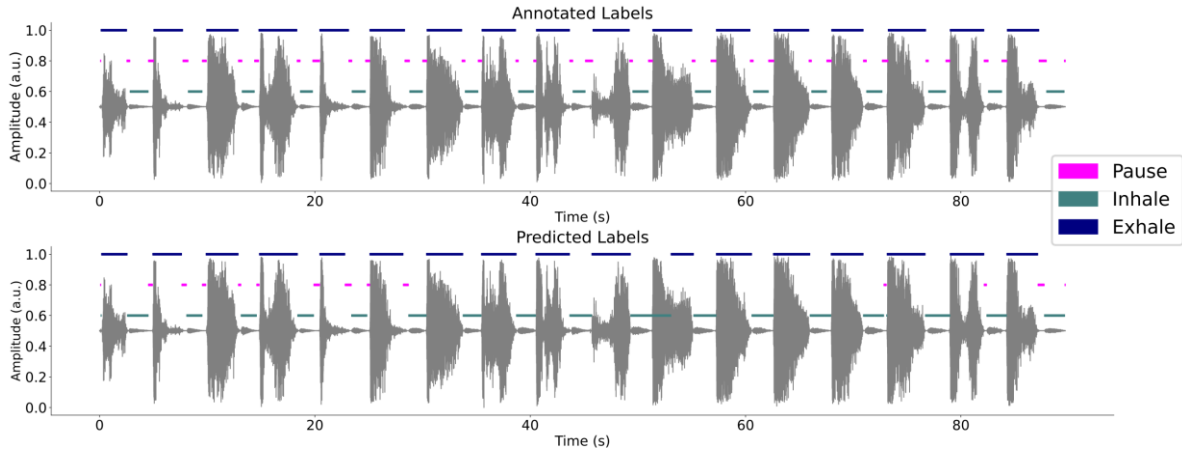


Figure 4: Sample signal with labels and the classifier prediction. This signal had an annotated IER of 0.47 and a predicted IER of 0.58 and a MAE in IER of 0.17.

4. Discussion

This work presents an epoch-by-epoch classification of inhalation, exhalation and respiratory pauses from audio signals recorded remotely using mobile devices in a cohort of 112 participants. Inhale and exhale duration and inhale-to-exhale ratio were estimated from the outputs of the classifier model. The comparison of protocol, devices, accuracy and absolute errors between this study and previous work is presented in Table 3.

The accuracy, precision, recall and f1-scores of the presented classifier, at 73.0%, are comparable with previous studies that reported accuracy of 75.5% [15] and 77% [16] when analyzing breathing patterns, Table 3. However, in [15], the data were collected in a laboratory setting and participants trained their breathing patterns to always follow the same inhale-pause-exhale-pause dynamics, thus allowing for extra assumptions when analyzing the data.

In contrast, our study includes spontaneous breathing data recorded remotely. In [16], a convolutional neural network approach was used and the classifier was trained using acoustic data and inertial sensor data. The same study [16] reports a binary (inhale/exhale) classification accuracy of 49% using random forests, based on audio data recorded by smartphones on the chest, while the present study achieved 73% accuracy using acoustic signals recorded close to the mouth and nose.

The reported classifier accuracy is lower than another study that analysed inhales and exhales in 125 participants, which reported accuracy of 93.2% [21]. However, in [21], the data were collected in a laboratory setting and the breathing patterns were controlled using breathing exercises, similar to [16], while our data were recorded at home. The f1 score for inhale

classification, 58.5%, was substantially lower than for exhale classification, 83%. A previous study using support vector machines to classify inhalation and exhalation reported f1 scores of 68% and 83%, respectively, in participants with respiratory conditions [26]. Though they report a higher f1 score for inhalation, that study did not consider pauses in the auditory signal, which can often be mistaken as inhales due to the inhale lower amplitude in the sound signal. Additionally, several previous studies [15], [16] employ neural network models to classify breathing patterns, which are less efficient and more complex than random forest, decreasing the interpretability of the results.

5. Conclusions

A computationally inexpensive approach to estimate respiration rate, inhale and exhale duration and inhale-to-exhale ratio, implementable in real-time is presented. The methods yielded an accuracy of 73% and low mean absolute error for respiration rate and inhale and exhale duration. In addition, inhale-to-exhale ratio can be estimated with low error for 76% of the recordings analysed. Data collection was performed by the participants in their own home using their own devices. The approach could be used for home-monitoring of respiration that can be easily deployed and for real time biofeedback applications.

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Table 3: Comparison of models from previous studies.

Model	Protocol	Devices	Accuracy	RR MAE/MAPE
F0 and RF: Present study	Real-life conditions in home	Participant smartphone	73%	0.63/4.6%
CNN [15]	Laboratory	Smartphone	75.5%	2.27/38.3 %
CNN [16]	Laboratory	Smartphone & chest band	77%	-/8.3 %
Acoustic analysis [21]	Laboratory	Microphone	93.2%	-
SVM [26]	Real-life hospital conditions	Smartphone	75.5%	-

F0: fundamental frequency method for RR; RF: Random forest; CNN: Convolutional Neural Network; SVM: Support vector machine

7. References

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