UBILUNG: MULTI-MODAL PASSIVE-BASED LUNG HEALTH ASSESSMENT

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ABSTRACT

Lung health assessment is traditionally done mainly through X-ray images and spirometry tests which are time-consuming, cumbersome, and costly. In this paper, we investigate the potential of passively recordable contents such as speech, cough and heart signal for such an assessment. Our regression model is the first in the literature to achieve mean absolute error (MAE) of 7.47% for estimation of forced expiratory volume in 1 sec. (FEV1) over forced vital capacity (FVC) ratio using these contents. This is comparable to the state of the art active phone-based spirometry methods. Additionally our classification models achieve a F1-score of 0.982 for healthy *v.s.* diseased, 0.881 for obstructive *v.s.* non-obstructive, 0.854 for chronic obstructive pulmonary disease (COPD) *v.s.* asthma, and 0.892 for severe *v.s.* non-severe obstruction classification.

Index Terms— Ridge Regression, Multi-Modal Learning, Lung Function Estimation

1. INTRODUCTION

Pulmonary disease is one of the major leading causes of mortality worldwide. According to a report in 2014 [1], the annual cost spent on the detection, treatment, and management of pulmonary diseases in the USA reaches up to $154 billion, among which COPD and asthma account for more than 85% of this expenditure. The number keeps climbing up over the past few years, especially due to the recent COVID-19 pandemic situation [2]. The advancements in mobile and wearable sensing enabled a range of modalities for pulmonary disease diagnosis and severity assessment, such as speech voice [3], breathing rate [4], walking pattern [5], and heart beat [6]. However, clinicians often need more fine-grained information such as lung function parameters for timely health condition monitoring. Medical-grade spirometry has been used as the gold standard to measures these parameters including FVC, FEV1, and FEV1/FVC (the obstruction status) of the patients. A traditional hospital spirometry is expensive, time-consuming, and impractical for frequent assessment and home-based spirometers are inaccurate mainly due to subject's failure to properly comply. As smartphones and wearable bio-trackers are becoming prevalent, there has been growing interest in developing new techniques for assessing the lung function via ubiquitous devices. For example, both SpiroSmart [7] and SpiroCall [8] proposed the use of mobile phones to measure the lung function by asking the user to blow air into a built-in microphone achieving 5.1% and 7.2% MAE on average. However, these methods are still demanding users to properly blow into the microphone as the blowing distance and angle can greatly affect the results. Moreover, due to the nature of this test, there exist the risk of potentially introducing dizziness, shortness of breath, and even possibly exacerbation to these subjects. Therefore, there is a growing call to develop a more passive solution for monitoring of the chronic pulmonary patients [9, 10] using modalities such as cough and speech exhibiting the potential for passive lung function estimation. However, all these works only took one single data type into account and therefore didn't reach acceptable accuracy. Our work expands passive input modalities and significantly outperforms these models. In addition, we used these modalities to perform 4 classification tasks to identify subject's condition and severity.

We propose Ubilung that leverages passively collectable modalities enabled by mobile/wearable devices to estimate the lung function, dismantling the requirement for any active engagement of the users. Specifically, Ubilung leverages two sensor signals: the audio signal from a microphone (cough and speech) and the blood volume pulse (BVP) signal from a PPG sensor (heart rate and heart rate variability, HR/HRV). A cough would typically involve an initial deep inspiration, the contraction of the expiratory muscles, and a sudden glottis opening with an explosive expiration, very similar to blowing process in a spirometry test [11, 9, 10]. In addition, recent research has shown the correlation between lung function and speech [12, 13], as well as HR/HRV [14]. To evaluate our models, we conducted two separate independent multi-modal data collection studies in collaboration with local hospitals. The contributions of our paper are as follows:

- We propose a novel lung function assessment method that leverages passively collectible contents from mobile/wearable devices: cough, speech, and HR/HRV.

Thanks to Brigham and Women Hospital for partnering with Samsung Research America for study design, patient recruitment and data collection.

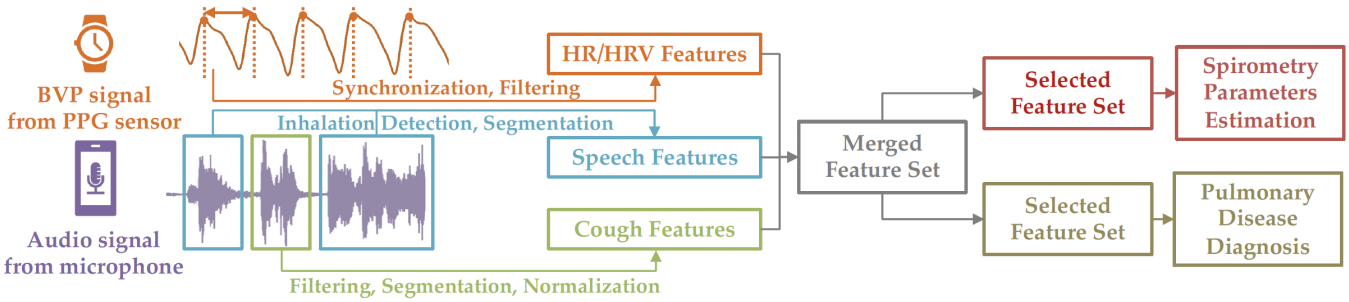

Fig. 1: Analysis pipeline combing cough, speech, and HR/HRV data.

- Our best model achieves an accuracy level close to the state-of-the-art mobile active spirometry methods.
- Our classification models were successful to classify a series of pulmonary condition/severity levels using these contents.

2. PROPOSED ALGORITHMS

In this section, we introduce Ubilung, our algorithm that is combining data from multiple passively collectable modalities comprising of preprocessing, feature extraction/selection and classification/regression model development. Figure 1 visualizes the overall analysis pipeline. Our audio preprocessing starts with a band-pass filter with 20Hz and 20KHz corner frequencies, since most human voice content frequency lies within this range [15, 16]. Then the filtered signal is normalized for amplitude and resolution per sample. We then extract different time-domain and frequency-domain features for each modality. For the cough, time-domain features such as duration, zero-crossing rate, interquartile range of the amplitude, mean, median, std, skew, and kurt were generated as well as frequency-domain feaures such as spread, centroid, flatness, rolloff), 20 mel frequency cepstral coefficients (MFCC), and 12 Chroma features. These features are calculated for each cough snippet separately. As a user has multiple cough periods, we further calculate aggregated statistics of all these features (min, max, mean, median, std, kurt) across the same user's cough data. For speech, we extracted two types of features: 1) acoustic features that can capture dysphonia, comorbidity commonly observed in pulmonary patients [17, 18]; and 2) pulmonary features to capture pulmonary obstruction. The former includes shimmer, jitter, and 20 MFCCs. The later includes pause duration and frequency, vocalization to inhalation ratio, average phonation time, inspiration sound energy, and harmonic-to-noise ratio (HNR). For the BVP signal from PPG sensors we conduct a series of preprocessing steps which is a combination of a low pass filter, slope sum, and decision rules to remove power line interference, motion artifact, baseline wander and premature ventricular contraction to obtain clean BVP signals [19, 6]. We then extract RR interval and normal RR interval (NN interval) from clean BVP data [20]. Then, instantaneous HR and a series of HRV features (both time-domain and frequency-domain) are calculated from NN interval sequences, such as pNN20 (NN20 count divided by the total number of all NN intervals, where NN20 is the number of pairs of adjacent NN intervals differing by more than 20 ms), total power, and approximate entropy. After concatenating features from all the modalities, our feature table consisted of a total of 376 features per subject. This could easily lead to the overfitting. Using a 2-layer feature selection, we first remove features with strong collinearity (pair-wise correlation ≥ 0.9). The second feature selection step differs based on the analysis task in the modeling stage.

Five most commonly used spirometry parameters are FVC, FEV1, FVC%, FEV1% (predicted percentage of volume values) and FEV1/FVC. More information on these pulmonary assessment metrics is given in [21]. In the feature selection step, we calculate Pearson correlation between each feature and the target, rank all features according to the correlation value, and choose features with correlation above 0.3 (including features with moderate or higher correlation). Linear, Lasso, ridge random forest, Bayesian and elasticNet regression methods with a grid search on number of features and model hyper-parameters were utilized to find the optimum model.

In addition to training regression models, we perform four classification tasks to further investigate the potential of our passive modalities for condition/severity assessment.

1. Identifying pulmonary patients (healthy *v.s.* diseased).
2. For all pulmonary patients, determining obstructive (FEV1/FVC < 0.7) *v.s.* not (FEV1/FVC ≥ 0.7) [22] (obstructive *v.s.* non-obstructive).
3. Classifying between two most common obstructive lung diseases (*i.e.*, COPD *v.s.* Asthma).
4. Finally, classifying obstruction severity of subjects (non-severe *v.s.* severe). We refer to the Global Initiative for Lung Disease (GOLD) criteria [23] for severity assessment: mild or moderate (FEV1 $\geq$ 50% predicted), severe or very severe (FEV1 $<$ 50% predicted).

For a classification task, we first perform a t-test between

classes for each feature. We then remove the features with p-value larger than 0.05 and select the best features based on mutual information [24] against each classification goal. The optimal set is determined in a grid search using 10-fold cross-validation on dataset1. The selected feature set is then introduced to several classification models including linear SVM, random forest, K nearest neighbors, logistic regression and multilayer perceptron and tested with different hyperparameters using a grid search to find the optimum model.

3. EXPERIMENTS

3.1. Dataset and Evaluation Metrics

We utilized two independent datasets to demonstrate the generalizability of our models. The training is from the first that is a controlled clinical study during patients' regular visits (dataset1) including 70 participants: 25 asthma, 25 COPD, 10 chronic cough (non-obstructive) and 10 healthy subjects. The second study was conducted during uncontrolled clinical visits with presence of larger amount of natural acoustic noise with 20 participants with asthmatic symptoms but unidentified condition going through a test called methacholine challenge (dataset2) [25]. Both groups showed diversity of lung function parameters. Both studies were conducted in hospital with the supervision of the pulmonologists and were approved by the Institutional Review Board (IRB). Among many other tasks, subjects went through a speech session (a given paragraph of text, 1-min), and a two-min voluntary cough session while holding a Samsung Note 8 smartphone in front of their mouth and wearing a Gear Sport smartwatch to record their PPG signal. Their lung function parameters were collected using a hospital-grade spirometer (Pneumotrac Portable Screening Spirometer- model 6800). Cough and speech sessions were manually listened to by trained annotators to segment out each cough and speech episodes using audacity toolbox. For all evaluation including both regression and classification tasks, we performed a random subject-level 80/20 split (subjects are exclusive in train/test). We repeated the process ten times to reduce noise and calculated the average test error as the final outcome. For regression tasks, MAE is calculated and for classification tasks we utilized F1-score to compare different models.

3.2. Evaluation Results

For the first experiment, we applied different regression models to selected features. Different sets of features were selected by the algorithm for different outcomes (23 cough, 5 speech and 2 HR for our best FEV1/FVC model for example). Ridge regression with ($\lambda = 1$) consistently performed best across all targets. Table 1 shows the results for this best model. Our best models achieved MAE of $0.605L$ on FVC and $0.438L$ on FEV1. For FVC% and FEV1%, our models achieved 11.15% and 11.84% error, respectively. As for FEF1/FVC, our best model achieve a mean error of 7.47% which is very similar to most of the state-of-the-art methods [7, 8, 26], (as can be seen in Table 1) but our method relies only on contents that can be passively collected.

Table 1: Best model regression results for the combination of all three modalities. The last three rows show the performance of current mobile spirometer techniques.

	FVC	FVC%	FEV1	FEV1%	FEV1/FVC
Min Value	1.47L	30%	0.69L	24%	31%
Max Value	5.93L	126%	4.63L	102%	91%
# of features	43	54	34	29	31
Mean Error	0.605L	11.15%	0.438L	11.84%	7.47%
SprioSmart [7]	-	-	-	-	5.10%
SpiroCall [8]	-	-	-	-	7.30%
ExhaleSense [26]	-	-	-	-	7.57%

Table 2: Regression results for different combinations of the data modalities. The three rows above the dashed line use single modality and are regarded as baselines.

Modality	FVC	FVC%	FEV1	FEV1%	FEV1/FVC
Cough [9, 10]	0.622L	12.67%	0.574L	15.77%	8.05%
Speech [13]	0.609L	13.42%	0.645L	16.73%	10.93%
HR/HRV	0.804L	15.70%	0.726L	15.70%	9.69%
Cough + Speech	**0.596L**	12.05%	0.457L	14.47%	8.51%
Cough + HR/HRV	0.651L	**10.24%**	0.484L	12.58%	8.20%
Speech + HR/HRV	0.659L	13.10%	0.655L	14.06%	9.65%
All	**0.605L**	**11.15%**	**0.438L**	**11.84%**	**7.47%**
Improvement against baseline: cough only	2.7%	12.0%	23.7%	24.6%	7.2%

Additionally, we investigated the regression results from the best model (Ridge regression ($\lambda = 1$)) for different combinations of different modalities as can be seen in in Table 2. It can be observed that combinations containing cough as one modality often have the lowest error. This matches with the theory that cough physiological procedure is very similar to spirometry (forced exhale of air out of lung). Also we can see that our method using all modalities achieves the best performance on FEV1, FEV1% and FEV1/FVC estimation, and the second-best on FVC and FVC% estimation that show all modalities can contribute to lung function estimation.

We also investigated the generalizability of our method by applying the best model trained from dataset1 (Ridge regression ($\lambda = 1$)) on the second dataset. This is a simulation of the real use case when applying a model on a new user's data collected from a new environment (Table 3). We can observe a drop in the performance (compared to Table 2). This is mainly due to the fact that the nature of the two datasets are quite different including but not limited to clinical supervisors, environments, background noises. Despite this drop, we can still see that compared to the best baseline model that only used cough sound, our cross-dataset model outperforms the FVC, FEV, and FEV1/FVC estimation by 19.6%, 8.5%, and 10.8%, respectively.

Table 3: Generalizability evaluation results trained on dataset1 and tested on dataset2. The three rows above the dashed line use single modality and are regarded as baselines.

Modality	FVC	FVC%	FEV1	FEV1%	FEV1/FVC
Cough [9, 10]	1.181L	**14.51%**	0.986L	19.24%	11.37%
Speech [13]	1.162L	25.13%	1.382L	27.36%	**10.14%**
HR/HRV	0.996L	22.26%	1.378L	36.70%	20.56%
Cough + Speech	0.987L	17.48%	**0.902L**	21.23%	12.23%
Cough + HR/HRV	0.961L	20.17%	0.961L	38.65%	20.37%
Speech + HR/HRV	1.010L	19.94%	1.005L	29.15%	14.04%
All	**0.950L**	**14.51%**	**0.902L**	**19.23%**	**10.14%**
Improvement against baseline: cough only	19.6%	0.0%	8.5%	0.1%	10.8%

Table 4: Classification results on pulmonary-related condition assessment using cough, speech and HR data.

	Healthy *v.s.* Diseased	Obstructive *v.s.* Non-obstructive	COPD *v.s.* Asthma	Non-severe *v.s.* Severe
# of feature	12	13	8	20
Accuracy	0.987	0.860	0.840	0.887
Precision	0.978	0.905	0.875	0.899
Recall	0.987	0.860	0.840	0.887
Balanced F1	0.982	0.881	0.854	0.892

For the next experiment, we looked into the four classification tasks mentioned in Section 2. The selected feature distribution among 3 modalities has been 63% cough, 24% speech and 13% HR averaged among all classification tasks. Table 4 presents the results from our best model (and its parameters), Random forest (100 trees, max depth 50), achieving F1-score of 0.982 on the healthy *v.s.* diseased task, 0.881 on the obstructive *v.s.* non-obstructive task, 0.854 on the COPD *v.s.* Asthma task, and 0.892 on the non-severe *v.s.* severe tasks. There is no passive-based benchmark in the literature to compare our results, but our performance is comparable to the previous work using active sensing modalities [28]. Similar to regression analysis, we also compared all possible combinations of the three modalities using the data in our dataset and summarized the results in Table 5. We listed the related reference work in the top three rows of Table 5 based on their data source as the baseline. They either used the same data source (cough sound or speech sound) or a similar source ([6] mainly used HR/HRV data from an ECG sensor on a chest-band rather than a PPG sensor from a smartwatch). There are a few interesting observations here. First, among the baselines single-modality models, cough model has the best overall classification performance. Cough appeared to be an effective modality, especially on the healthy *v.s.* diseased task. Second, for classification tasks, the contribution proportions of the three modalities are consistent, with the order cough $>$ speech $>$ HR. This is supported by the performance order of row 1-3, as well as the order of row 4-6 (which can be viewed as feature ablation [29]). Lastly and most importantly, our method significantly outperforms the best baseline models on the F1-score by 0.120 on the obstructive *v.s.* non-obstructive task, 0.078 on the COPD *v.s.* Asthma task, and 0.087 on the non-severe *v.s.* severe task.

Table 5: F1-score for pulmonary-related condition assessment using combinations of modalities. The rows above dashed line use single modality and are regarded as baselines.

	Healthy *v.s.* Diseased	Obstructive *v.s.* Non-obstructive	COPD *v.s.* Asthma	Non-severe *v.s.* Severe
Cough [10, 9, 27]	**0.982**	0.807	0.776	0.805
Speech [3]	0.912	0.721	0.770	0.777
HR/HRV [6]	0.812	0.618	0.682	0.672
Cough + Speech	**0.982**	0.832	0.820	0.875
Cough + HR/HRV	**0.982**	0.823	0.807	0.871
Speech + HR/HRV	0.930	0.651	0.826	0.787
All	**0.982**	**0.881**	**0.854**	**0.892**
Improvement against baseline: cough only	0.0%	9.2%	10.1%	10.8%

We also tested the generalizability of our method on the classification tasks. However, as described in Section 3.1, our second dataset only contains spirometry test results from participants but not the clinical diagnosis. Thus we could only validate on the obstructive *v.s.* non-obstructive task and the non-severe *v.s.* severe task. Our model achieves F1-scores of 0.782 and 1.000 on these two tasks, while the best baseline model (using speech only [3]) has 0.730 and 1.000. Since all participants were non-obstructive and non-severe in dataset2, these results have limited reliability.

4. CONCLUSION

In this paper, we propose UbiLung, leveraging multi-modal analysis for lung health assessment using passively collectable contents. Our method uses cough, speech, and HR/HRV that can be easily obtained on ubiquitous devices (microphones and PPG sensors). We utilized our technique for spirometry parameter estimation and pulmonary condition/severity diagnosis. Our method consistently achieves good performance. For parameter estimation, our best model significantly outperforms the best baseline model by 2.7% on FVC measure, 12.0% on FVC% measure, 23.7% on FEV1 measure, 24.6% on FEV1% measure and 7.2% on FEV1/FVC measure. Our final estimation accuracy is comparable to that of the state-of-the-art active mobile spirometer techniques. As for the disease diagnosis, our model significantly outperforms previous work by 9.2% on the obstructive *v.s.* non-obstructive task, 10.1% on the COPD *v.s.* asthma task, 10.8% on the non-severe *v.s.* severe task. These results indicate that combining these passively collectible contents provides a great opportunity for longitudinal monitoring of lung health. However, for future work, it is essential to evaluate these models when applied to involuntary passive contents that are automatically segmented out from the passive field data.

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