Coswara - A Database of Breathing, Cough, and Voice Sounds for COVID-19 Diagnosis

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Abstract

The COVID-19 pandemic presents global challenges transcending boundaries of country, race, religion, and economy. The current gold standard method for COVID-19 detection is the reverse transcription polymerase chain reaction (RT-PCR) testing. However, this method is expensive, time-consuming, and violates social distancing. Also, as the pandemic is expected to stay for a while, there is a need for an alternate diagnosis tool which overcomes these limitations, and is deployable at a large scale. The prominent symptoms of COVID-19 include cough and breathing difficulties. We foresee that respiratory sounds, when analyzed using machine learning techniques, can provide useful insights, enabling the design of a diagnostic tool. Towards this, the paper presents an early effort in creating (and analyzing) a database, called Coswara, of respiratory sounds, namely, cough, breath, and voice. The sound samples are collected via worldwide crowdsourcing using a website application. The curated dataset is released as open access. As the pandemic is evolving, the data collection and analysis is a work in progress. We believe that insights from analysis of Coswara can be effective in enabling sound based technology solutions for point-of-care diagnosis of respiratory infection, and in the near future this can help to diagnose COVID-19.

Index Terms: COVID-19, Cough, Breath, Voice, Random Forest

1. Introduction

The COVID-19 is a respiratory infection caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [1]. The disease, officially declared a pandemic, has infected millions of humans across the globe, and has a fatality rate between 1–10% in most countries. Fig. 1 shows the cumulative number of cases (and casualities) [as of May 15, 2020], and there is still no sign of flattening. This trajectory of growth started on 11 Jan 2020, and has forced many countries to take serious containment measures such as nation-wide lockdowns and scaling up of the isolation facilities in hospitals. The lockdown is useful as it gives time for large scale testing of individuals. The gold standard for COVID-19 diagnosis is the reverse transcription polymerase chain reaction (RT-PCR) test of infected secretions (from nasal or throat cavity). The results of a RT-PCR test are available in 48 hours. The limitations of the testing include: (i) violation of social distancing which increases the chance of infection spread, (ii) expenses involved in the chemical reagents and devices, (iii) testing time in hours and needs expertise, and (iv) difficulty in large scale deployment. Forseeing a rise in number of COVID-19 cases, this has also led to a spurt in proposals on technology solutions for healthcare. Specifically, the need for the development of simplistic, cost effective and fast testing, yet accurate methodologies for infection diagnosis has become crucial for healthcare, policy making, and economic revival in several countries. The focus is also on point-of-care diagnostic tools, technology solutions which can be deployed rapidly, pre-screening tools, and cheaper alternatives to RT-PCR test, overcoming the limitations of chemical testing.

The research and the understanding of the novel virus and COVID-19 is a work in progress at various laboratories around the world. As of 16th May, the WHO and the CDC have listed dry cough, difficulty in breathing, chest pain (or pressure), and loss of speech or movement as key symptoms of this viral infection, visible between 2 – 14 days after exposure to the virus. Also, a recent modeling study of symptoms data collected from a pool of 7178 COVID-19 positive individuals validated the presence of these symptoms, and proposed a real-time prediction and tracking approach [2]. Medical literature shows that speech breathing patterns are intricately tied to changes in anatomy and physiology of the respiratory system [3]. Drawn by these observations, we identify an opportunity to make impact on point-of-care diagnosis using speech and acoustics research. Bringing together a large dataset of respiratory sounds, machine learning, and respiratory infection expertise from doctors can help in evaluating the potential in using respiratory sound samples for diagnosis of COVID-19. The goal is not to replace the existing chemical testing methodologies but to supplement them with a cost effective, fast and simpler techniques.

This paper presents our efforts launched along this direction. The project is named Coswara, a combination of the words COVID-19 and Swara (sound in Sanskrit). The scientific rationale behind the conception of this project is presented in Section 2. Section 3 presents an overview of the project. In Section 4, a summary of the dataset collected and released openly as of 5 May 2020 is presented. We conclude with a discussion.
2. Scientific Rationale

2.1. Cough Sounds

Cough is a powerful reflex mechanism for the clearance of the central airways (trachea and the main stem bronchi) of inhaled and secreted material. Typically, it follows a well defined pattern, with an initial inspiration, glottal closure and development of high thoracic pressure, followed by an explosive expiratory flow as the glottis opens with continued expiratory effort [4]. The reflex is initiated by cough receptors within the central airways that are sensitive to both mechanical and chemical stimuli. Sound is generated during cough by air turbulence, vibration of the tissue, and movement of fluid through the airways [5]. This turbulence generates sound with a broadband “noisy” character, whose frequency content depends on the velocity, density of the gas, and dimensions of the airways from source till the mouth. A cough sound is usually composed of three temporal phases: explosive, intermediate, and voicing phase. Fig. 2(b) shows a wideband spectrogram of a sequence of three heavy cough sound signals. Each cough lasts close to 300 ms, and the spectrum exhibits broad spectral spread over 500 Hz, 1.5 kHz, and 3.8 kHz. Interestingly, over one hundred pathological conditions are associated with cough [6]. The acoustic features of a cough sound depend on the air flow velocity as well as the dimensions of vocal tract and airways [4]. This makes it possible to detect cough sounds [7] in audio recordings. As the physical structure of the respiratory system gets altered with respiratory infections, it is even possible to classify pathological condition based on a cough sound. Pertussis is a contagious respiratory disease which mainly affects young children and can be fatal if left untreated. Pramono et. al [8] presented an algorithm for automated diagnosis of pertussis using audio signals by analyzing cough and whoop sounds. Several other recent studies have attempted to identify chronic obstructive pulmonary disease (COPD) (a disease caused primarily due to smoking) [9], and tuberculosis (an infectious disease usually caused by mycobacterium tuberculosis (MTB) bacteria that affects the lungs) [10]. In addition, for respiratory disorders like asthma and pneumonia, algorithms based on cough sounds recorded using a smartphone provides a high level of accuracy [11]. For Covid-19 detection and diagnostics, the research initiatives from University of Cambridge [12], Carnegie Mellon University [13], Wadhwani AI institute [14] and a project from EPFL [15] have already been launched. Also, a recent work by Imran et al. [16] suggests a good accuracy for cough based detection of COVID-19 using a preliminary investigation with a small number of subjects.

2.2. Breath sounds

Breathing difficulty is another common symptom for COVID-19. This is often exhibited as a shortness of breath. The early work by Anderson et. al [17] reported that the spectrogram of breath sounds captured by a smartphone shows distinct patterns for asthmatic conditions compared to healthy individuals. For the diagnostics of COVID-19, the use of breathe sounds is also being attempted by a research group at New York University [18]. Fig. 2(c) shows the wide-band spectrograms of inhaling and exhaling cycles while breathing.

2.3. Voice sounds

The studies show that lung diseases have distinct biomarkers in the speech breathing cycles [19]. The study reported in [20] showed that phonation threshold pressure (PTP), a quantifiable measure defined as the minimal lung pressure required to initiate and sustain vocal fold oscillation, is correlated with vocal fatigue. The impact of laryngeal dysfunction in breathing patterns of read speech was analyzed in [21]. Fig. 2(a) depicts the spectrogram of a sustained phonation of /a/ vowel (as in cat). In contrast to cough and breath sound sample, there is a clear voicing seen as harmonics and localized concentration of energy at regions defined by formants.

3. Coswara Overview

Coswara [22] is an attempt to provide a simple and cost effective tool for diagnosis of COVID-19 using breath, cough and speech sounds. As most of the major symptoms of the disease include respiratory problems, the proposed project aims to detect and quantify the biomarkers of the disease in the acoustics of the these sounds. The project has three stages, depicted in Fig. 3. Below we briefly describe each stage.

3.1. Data collection

The goal is to create a dataset of sound samples from healthy and unhealthy individuals, including those identified as COVID-19. For sound data, we focus on nine different categories, namely, breathing (two kinds; shallow and deep), cough (two...
Figure 3: Different stages in the proposed Coswara project - (1) Data collection, (2) Modeling, (3) Diagnostic tool development.

Kinds; shallow and heavy), sustained vowel phonation (three kinds; /æ/ as in made, /ı/ as in kit, /u:/ as in goose), and one to twenty digit counting (two kinds; normal and fast paced). We also collect some metadata information, namely, age, gender, location (country, state/province), current health status (healthy / exposed / cured / infected) and the presence of comorbidities (pre-existing medical conditions). No personally identifiable information is collected. The data is also anonymized during storage.

3.2. Modeling
The collected data will be analysed using signal processing and machine learning techniques. The goal is to build mathematical models aiding identification of biomarkers from sound samples. This stage is a work-in-progress while we create the dataset. We have also initiated regular release of the curated dataset as open access via GitHub platform.

3.3. Diagnosis tool
We aim to release the diagnosis tool as a web/mobile application. The application prompts the user to record voice samples, similar to the dataset collection stage, and provides a score indicating the probability of COVID-19 infection. The final deployment of tool is subject to validation with clinical findings, and authorization/approval from competent healthcare authorities. Given the highly simplistic and cost effective nature of the tool, we hypothesize that, even a partial success for the tool would enable a massive deployment as a first line diagnostic tool to pre-screen the infection.

4. Dataset Description
The project is currently ongoing. The collection, release, and analysis of the dataset are in progress. Below we provide a description of the most recent release of the dataset.

4.1. Data collection methodology
The data collection strategy focussed on reaching out to the human population across the globe. For this, we created a website application providing a simple and interactive user interface. A user could open the application in a web browser (in laptop or mobile phone), provide metadata, and proceed to recording the sound samples using the device microphone. The average interaction time with the application is 5 - 7 mins. The user was prompted to use personal device and wipe off the device with a sanitizer before and after recording, and keep the device 10 cm from the mouth during recording.

4.2. Metadata description
The currently released dataset has a participant count of 570. Fig. shows the distribution of the participants across gender, age, country (India and outside), Indian states, and health status (healthy and unhealthy). Each participant provides 9 audio files corresponding to the different categories.

4.3. Annotation
The audio files in the dataset were manually curated and a predefined set of criteria was used to verify the audio quality. The annotation was done using a custom designed web interface where the audio file was played and questions that the annotator had to answer. The questions included information about the quality of the audio file, whether the audio file belonged to the appropriate category (shallow cough, breathing deep, etc.) and if the audio file was in a noisy environment. The annotator was also allowed to give additional comments to each audio file. Fig. depicts the quality count of the recordings across the nine categories. In total, the dataset has 3470 clean and 1055 noisy, and remaining unusable (bad) audio recordings.

The dataset can be accessed at https://github.com/iiscleap/Coswara-Data
Figure 4: Metadata of the Coswara database: Participant pool count across (a) gender, (b) country, (c) health status, and (d) Indian states (only top 5 are shown), (e) age, and (f) sound category.

Figure 5: Confusion matrix (on test data) obtained on classifying 9 categories of sounds using a random forest classifier.

4.4. Acoustic Properties

The 9 sound categories (or classes) were chosen to capture the different physical states of the respiratory system using just the sound samples. We tested the complimentarity across these sound categories by building a multi-class classifier trained and tested on acoustic features extracted from the sound samples.

From the curated dataset, the clean audio recordings across participants were pooled and grouped by sound categories. A set of 9 different short-time (25 msec, with hop of 10 msec) temporal and spectral acoustic features were extracted from the audio files. These features included spectral contrast (7-D), MFCCs (13-D), spectral roll-off (1-D), spectral centroid (1-D), mean square energy (1-D), polynomial fit to the spectrum (2-D), zero-crossing rate (1-D), spectral bandwidth (1-D), and spectral flatness (1-D). After concatenation, this resulted in a 28-D feature for every 25 msec segment of audio. A random forest classifier was trained on a 70% - 30% train-test split for classifying every 25 msec segment into one of the nine sound categories. Fig. 5 shows resulting confusion matrix for the test data. All classes have the equal share in the test data (11.11%). It is interesting to note that the vowels are less confused, and the digit counting samples are more confused between themselves. This is also the case for cough samples and breathing samples.

5. Conclusion

We have described our efforts towards a sound based diagnostic tool for COVID-19. The tool, named Coswara, built upon prior studies that have shown good accuracy for detecting other respiratory disorders like asthma, pertussis, tuberculosis and pneumonia. We highlight the rationale for choosing different stimuli in the Coswara database. The progress in data collection in terms of meta data statistics are described. We also highlight the complimentary nature of the stimuli chosen. The next phase in the diagnostic tool development will attempt the use of machine learning algorithms to classify different health conditions and try to identify sound based biomarkers for Covid-19.

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