

# Does Facemask Impact Diagnostic During Pulmonary Auscultation ?

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**Abstract:** Facemasks have been widely used in hospitals, especially since the emergence of the coronavirus 2019 (COVID-19) pandemic, often severely affecting respiratory functions. Masks protect patients from contagious airborne transmission, and are thus more specifically important for chronic respiratory disease (CRD) patients. However, masks also increase air resistance and thus work of breathing, which may impact pulmonary auscultation and diagnostic acuity, the primary respiratory examination. This study is the first to assess the impact of facemasks on clinical auscultation diagnostic.

Lung sounds from 29 patients were digitally recorded using an electronic stethoscope. For each patient, one recording was taken wearing a surgical mask and one without. Recorded signals were segmented in breath cycles using an autocorrelation algorithm. In total, 87 breath cycles were identified from sounds with mask, and 82 without mask. Time-frequency analysis of the signals was used to extract comparison features such as peak frequency, median frequency, band power, or spectral integration.

All the features extracted in frequency content, its evolution, or power did not significantly differ between respiratory cycles with or without mask. This early stage study thus suggests minor impact on clinical diagnostic outcomes in pulmonary auscultation. However, further analysis is necessary such as adventitious sounds characteristics differences with or without mask, to determine if facemask could lead to no discernible diagnostic outcome in clinical practice.

*Keywords:* Lung sounds, Breath sounds, Auscultation, Universal Masking, Facemask, Spectrogram.

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## 1. INTRODUCTION

The COVID-19 pandemic led to the general requirement to wear a facemask for hospital patients and out in many countries (Klompas et al., 2020, Quintana-Diaz et al., 2020). Facemasks offer protection from contagious airborne transmission, and are especially important for patients with chronic respiratory disease (CRD) or chronic obstructive pulmonary disorder (COPD), as the virus directly deteriorates respiratory function (Grasselli et al., 2020, Marini et al., 2020). Facemasks thus offer CRD patients significant protection from COVID-19 and similar respiratory diseases for which their CRD is a significant co-morbidity (Echave-Sustaeta et al., 2014, Guiot et al., 2020a, Rijken et al., 2005). In particular, the prevalence of COVID-19 patients with CRD or COPD was higher in the United States and Europe, than their prevalence in the general population (Bouazza et al., 2021, Docherty et al., 2020, Richardson et al., 2020).

More than one year after the World Health Organization (WHO) officially declared de COVID-19 pandemic, it is still uncertain when and whether it will stop. Based on all the decisions and outcomes to date, it is likely universal masking mandates will become part of daily life, particularly in hospitals (Klompas et al., 2020, Quintana-Diaz et al., 2020). However, their clinical impact on diagnosis and care has been little addressed (Hopkins et al., 2021). Safety concerns related

to increased breathing resistance and thus work of breathing, altered pulmonary gas exchange, and other physiological parameters are only just now emerging (Hopkins et al., 2021, Samannan et al., 2021).

To date, there is currently no evidence supporting facemasks significantly reducing oxygenation or increasing CO<sub>2</sub>. In a recent literature review, wearing a facemask during physical activity was associated with negligible effects on work of breathing, pulmonary gas exchange, and other physiological parameters, regardless of the type of mask (Hopkins et al., 2021). A study comparing physiological parameters in 15 severe COPD patients suggests no significant difference in gas exchange with the use of surgical masks (Samannan et al., 2021). Hence, masks are currently recommended for all CRD patients with COPD or asthma, and often all patients.

While the impact of masks on physiological parameters has been briefly assessed, no study has ever examined the impact of facemasks on transmitted sounds in pulmonary auscultation, the primary form of respiratory examination. Pulmonary auscultation is the fundamental clinical tool for diagnosis, monitoring and treatment of respiratory pathologies of CRD patients (Andres et al., 2018, Guiot et al., 2020b). Medical staff use stethoscopes to listen to respiratory sounds via a slow deep oral inspiration. However, due to their increased airflow

resistance, facemasks may change lung sounds, reducing or altering diagnostic acuity and creating the conditions for reduced care and outcomes, and increased clinical effort.

This study thus aims to determine the impact of wearing facemasks on clinical patient evaluation, by comparing pulmonary sounds of patients with and without facemasks. It is a major first step towards assessing the diagnostic impact of universal masking mandates.

## 2. METHODS

### 2.1 Pulmonary auscultation

Pulmonary auscultation is commonly performed using stethoscopes to listen to lung sounds and identify potential lung and airway obstruction, characterized by adventitious sounds such as wheezes, crackles, or squawks, which are all clinically defined terms in this field (Andres et al., 2018). Each of these sounds has known minimum time duration and frequency ranges, and are associated with specific diseases and breathing phase. Hence, they provide a known standard for comparison.

Current electronic stethoscopes allow digital recording of lung sounds, offering the opportunity to provide new approaches in automated classification of recorded lung sounds (Andres et al., 2018, Nabi et al., 2019, Rodgers et al., 2017, Young et al., 2015). However, given the wide range of factors potentially affecting recorded sounds, including environmental conditions, demographics, recording location, classification algorithm systems are often very research area specific.

Current approaches for lung sounds are relatively recent, and focus on machine learning or statistical approaches (Kandaswamy et al., 2004, Ma et al., 2019, Sengupta et al., 2016, Serbes et al., 2017). None considered masked patients, though unmasked patient data exists (Rocha et al., 2019). Hence, the proposed study is novel.

### 2.2 Patients and data acquisition

This study uses a 3M Littmann® electronic stethoscope model 3200. This stethoscope allows to record lung sounds on a computer, and choose between different filters to export the data into a usable format. Unfortunately, the raw signal is not available for direct, custom filtering. Data is sampled at 4 kHz, where lung sounds typically range between 100-1000 Hz when captured over the chest, allowing frequency analysis and filtering without loss of signal in this range.

Lung sounds were recorded, to date, from 29 patients under informed consent. The local ethics committee of the University Hospital of Liège, Belgium, approved this observational prospective study. For each patient, one recording is made wearing a surgical mask and one without. Of these 29 patients, 3 were diagnosed with asthma, 12 with COPD, 1 with COVID-19, 2 with fibrosis, 1 with pulmonary arterial hypertension (PAH), 1 with pleurisy, and 2 with systemic sclerosis, and the remaining 7 patients were control patients with no particular lung problem. Demographics are given in Table 1.

The recordings were taken by an experienced lung specialist and data exported in .WAV format using the Diaphragm filter (amplifying sounds from 20-2000 Hz and emphasizing sounds between 100-500Hz) in the Littmann® StethAssist™ software. All recordings were taken at the left inferior lobe site, on the posterior side of the sitting patient. Recordings typically last 15 seconds, covering 3-4 breathing cycles.

Table 1. Patients recording summary

Patient Diagnosis	Number (%)
Healthy patients	7 (24)
Asthma patients	3 (10)
COPD patients	12 (41)
COVID-19 patients	1 (3)
Fibrosis patients	2 (7)
PAH patients	1 (3)
Pleurisy patients	1 (3)
Systemic Sclerosis patients	2 (7)
<b>Total</b>	<b>29 (100)</b>

### 2.3 Signal Processing

#### 2.3.1 Raw signal filtering

Lung sounds typically range between 100-1000 Hz (Andres et al., 2018). A zero-phase, forward and reverse digital 6<sup>th</sup> order Butterworth bandpass filter between 100-1500 Hz was applied to the raw signal (Figure 1). This filter also removes unwanted noises, such as low frequency heart sounds (~1-2 Hz).

#### 2.3.2 Segmentation

Recordings were segmented into individual breaths using a maximum autocorrelation function described in (Niu et al., 2018). The maximum autocorrelation is computed for the entire signal, and two thresholds (T1 and T2) are used to identify the beginning and the end of each breathing cycle. The start of inspiration is identified when the autocorrelation crosses the first and second threshold. The end of the expiration is identified when the autocorrelation drops back down below the lowest threshold, for more than 250 ms. An example is shown in Figure 1.

This segmentation process was supervised in this preliminary analysis, because some respiratory cycles were badly segmented using the thresholds of (Niu et al., 2018), which are data-specific, and not always appropriate due to variability. An example of the issue is shown in Figure 2, where the assumption that the first 250ms of the signal do not contain any breathing does not hold. This supervision does not impact the generality of the results.

#### 2.3.3 Feature extraction

Periodogram and spectrogram algorithms can be used to analyze and extract statistics of the signal (Andres et al., 2018, Li et al., 2017, Niu et al., 2018). While the periodogram provides information of the power spectrum for each frequency in the signal, the spectrogram provides added information on its time evolution as shown in Figures 3-4 for example sounds.

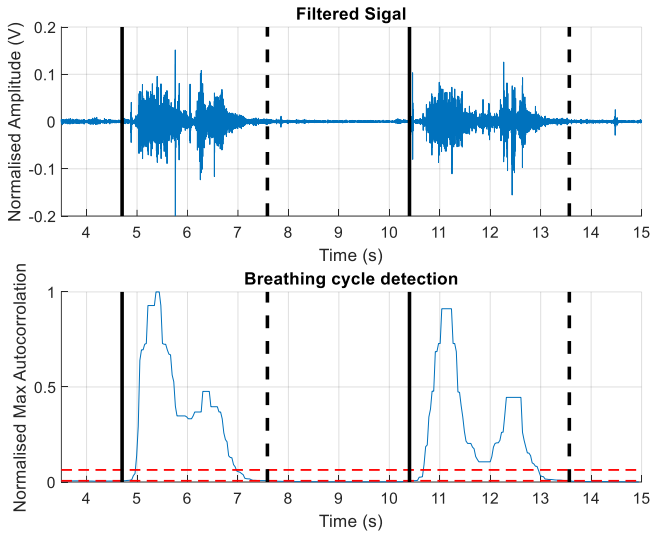


Figure 1. Segmentation of respiratory cycles. The beginning is represented by a solid black vertical line, and the end by a dashed black vertical line. All cycles are identified accurately.

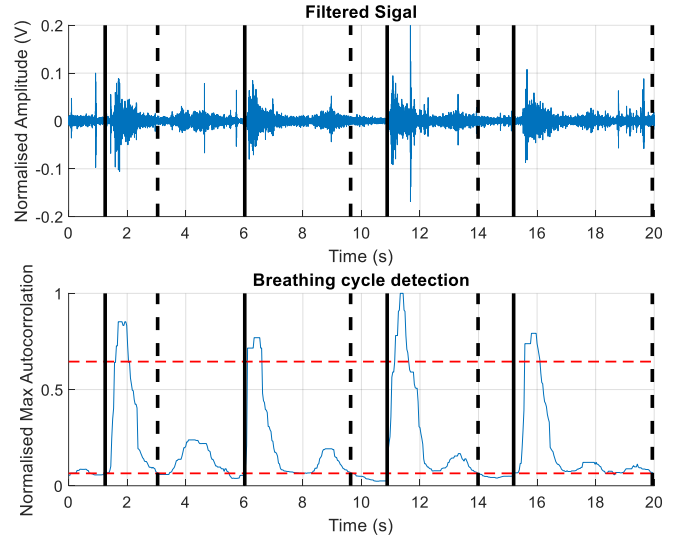


Figure 2. Segmentation for a respiratory cycle. The beginning is represented by a solid black vertical line, and the end by a dashed black vertical line. The first breath cycle is mis-identified.

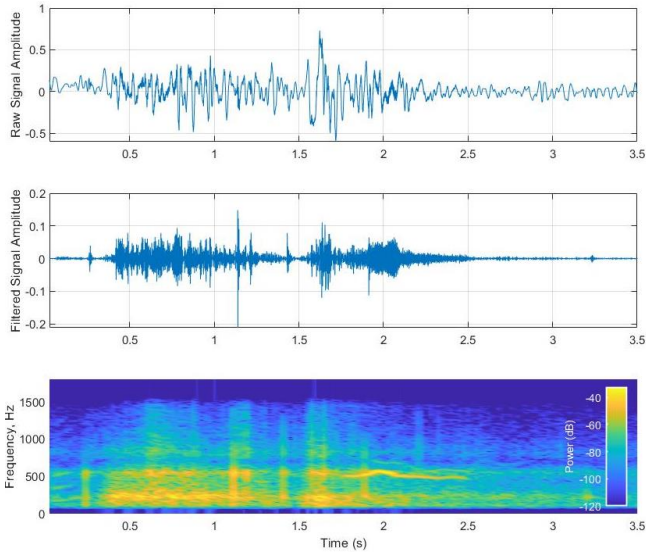


Figure 3. Raw signal (top), filtered signal (middle) and spectrogram (bottom) of an asthmatic patient breath with mask. A long 600ms wheeze at 500 Hz can be seen around  $t=2$ s.

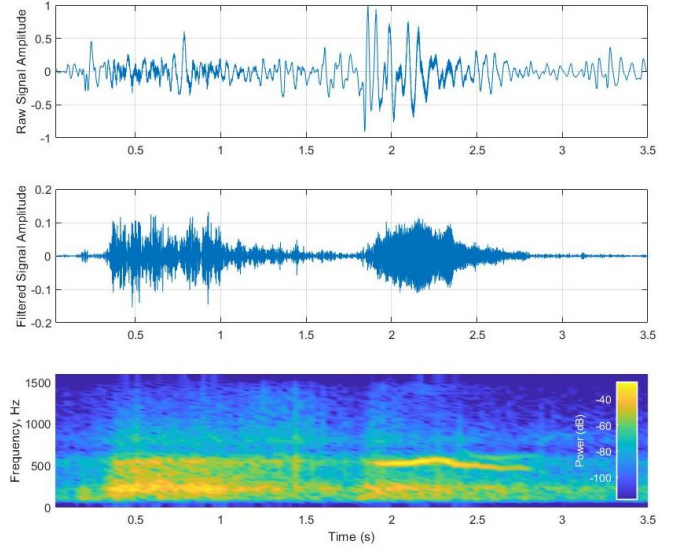


Figure 4. Raw signal (top), filtered signal (middle) and spectrogram (bottom) of asthmatic patient breath without mask. A long 900ms wheeze at 530 Hz can be seen around  $t=2.25$ s.

Spectrogram methods thus use short-time Fourier transforms (STFT) resulting in a time-frequency distribution of the signal. The window characteristics (length, overlapping, type of window) are often based on the specific features parameters to extract or highlight specific behavior in the signal. In this study, a 64ms Hamming window with 50% overlapping was used for signal framing, which is typical in lungs sounds analysis (Niu et al., 2018).

The average power of each breath signal in the 100-1000 Hz is computed, as well as the median spectral integration between 0-250Hz ( $SI_{0-250}$ ), 250-500Hz ( $SI_{250-500}$ ), and 500-1000Hz ( $SI_{500-1000}$ ) (Li et al., 2017). These ranges better distribute signal power in the time-frequency domain for each window in the spectrogram. In addition, the L-2 norm of the signal is computed, and peak and median frequency calculated.

### 3. RESULTS

In total, 87 breath cycles were identified from recordings with mask, and 82 breath cycles in recordings without masks across the 29 patients ( $\sim 3$  per patient, per case). The median [IQR] length for each breath cycles was 3.1 [2.5-4.1] s with a mask and 3.3 [2.5-3.9] s without. All results are in Table 2.

The L2-norm of the signal did not significantly differ between the two groups, with a median [IQR] of 1.01 [0.59-1.77] with mask and 1.09 [0.53-1.75] without mask. The peak frequency was also not statistically different with median [IQR] 223 [217-227] Hz and 224 [217-230] Hz with and without mask respectively, nor was the median frequency (222 [219-228] Hz vs. 223 [217-230] Hz, respectively).

When comparing the average power between 100-1000 Hz in the signal for each breath cycle, a median [IQR] of  $0.07 [0.03-0.15] \times 10^{-3}$  W and  $0.08 [0.02-0.16] \times 10^{-3}$  W are observed. Finally, there was also no significant differences in the median time-frequency spectral integration in 0-250Hz ( $0.33 [0.15-0.77] \times 10^{-3}$  vs.  $0.36 [0.10-0.75] \times 10^{-3}$ ), 250-500Hz ( $0.07 [0.03-0.12] \times 10^{-3}$  vs.  $0.06 [0.02-0.12] \times 10^{-3}$ ), and 500-1000Hz ( $0.13 [0.08-0.23] \times 10^{-3}$  vs.  $0.11 [0.05-0.25] \times 10^{-3}$ ).

**Table 2 – Results summary. Data is given as median [IQR] where appropriate. Hypothesis testing (distributions have equal medians) using the Mann-Whitney U test ( $P < 0.05$  is considered statistically significant). SI = Spectral Integration.**

	Mask	No Mask	P-val.
<b>Breath cycles</b>	87	82	/
<b>Breath length (s)</b>	3.1 [2.5-4.1]	3.3 [2.5-3.9]	>0.05
<b>Peak frequency (Hz)</b>	223 [217-227]	224 [217-230]	>0.05
<b>Median frequency (Hz)</b>	222 [219-228]	223 [217-230]	>0.05
<b>L2-Norm</b>	1.01 [0.59-1.77]	1.09 [0.53-1.75]	>0.05
<b>Average 100-1000 Hz Band Power (W)</b>	$0.07 [0.03-0.15] \times 10^{-3}$	$0.08 [0.02-0.16] \times 10^{-3}$	>0.05
<b>Median SI<sub>0-250</sub></b>	$0.33 [0.15-0.77] \times 10^{-3}$	$0.36 [0.10-0.75] \times 10^{-3}$	>0.05
<b>Median SI<sub>250-500</sub></b>	$0.07 [0.03-0.12] \times 10^{-3}$	$0.06 [0.02-0.12] \times 10^{-3}$	>0.05
<b>Median SI<sub>500-1000</sub></b>	$0.13 [0.08-0.23] \times 10^{-3}$	$0.11 [0.05-0.25] \times 10^{-3}$	>0.05

#### 4. DISCUSSION

This study is motivated by the hypothesis that increased resistance induced by a facemask may affect clinical diagnostic lung sounds in pulmonary auscultation. This increased resistance induces increased expiratory pressure at the mouth, and patients may be unknowingly compensating by increasing work of breathing to optimize gas exchange. Therefore, it is possible a COPD or asthmatic patient lung sound would be impacted by the mask.

The results of this early stage study do not show any significant difference in the features extracted between lung sounds in patients wearing a surgical mask or without a mask. However, more work is necessary to better assess whether universal masking may impact respiratory disease diagnostics. In particular, while frequency content and power do not vary, the perceived sound by the clinician may differ from the objective metrics presented, creating a diagnostic bias.

Compared to studies in the field of lung sounds analysis, our recordings seem of lower quality. Increased recording quality could be achieved, but this first attempt in comparing lung sounds aimed at using lung sounds as in a real environment. In particular, pulmonary auscultation is a desired approach due to its simple and low-cost requirements.

Due to not taking recordings in soundproof environments or with very high-quality microphones, the recordings used may

content unwanted environmental noise, such as room ventilation. In general, there is a desire for automation, where most research studies always used recordings from ideal situations, including recordings always starting with no breathing sounds, no coughing in the signal, and other restrictions which are not clinically feasible for CRD compromised patients. Thus, this work is biased towards clinically feasible alternatives with direct replacement, and does not control the environmental noises. Future work should balance whether using more restriction on how lung sounds are recorded to improve quality is necessary to respond to this research question, and whether such choices would translate to clinically feasible solutions.

In the results presented, respiratory sounds are compared between two groups (with and without mask). Future analysis should also compare specific sub-groups of patients with different diagnostics, as sounds can vary significantly in intensity and frequency content. Such a larger dataset may identify specific groups of patients where it may have an impact or show the minimal impact found in this study. For example, there could be a significant impact in patients with known respiratory deficiencies, such as asthmatic or COPD patients, as their respiratory functions are already decreased (Hopkins et al., 2021), when compared to healthy patients. However, much more recordings for all types of CRD patients are required and this study did not have the necessary power to achieve this outcome.

More features could also be used to further identify differences. For example, while there might not be any differences in the time-frequency domain of the signal, there could be differences in specific adventitious sounds characteristics. In the patient presented in Figures 3-4 for example, wearing a mask could impact the length and the frequency of the wheeze observed. This wheeze sound could appear when wearing a mask based on the result presented here, as the patient compensate and increase work breathing, and still yielding the sound. However, specific frequency content of these sounds has not been assessed with and without masks for a given patient.

It is also important to note the recordings for this preliminary study were taken using surgical masks. More work will be carried out to analyze the potential impact of higher protecting masks such as FFP-2 masks. These masks are designed to filter airborne particles and thus have higher air resistance. Lung sounds analysis wearing these masks could thus have higher impact when worn.

#### 5. CONCLUSIONS

In this early stage study comparing lung sounds in patients wearing a surgical mask or not, no significant difference was observed in frequency content, its evolution, or power, suggesting minor impact on clinical diagnostic outcomes in pulmonary auscultation. However, more work is required to further investigate the potential impact of universal masking on clinical respiratory diagnostics, including whether these objective measures translate to no discernible diagnostic outcome in clinical practice.



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