Validation of the LEOSound Cough Detection Algorithm

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Abstract

Background

Cough is an important respiratory symptom being of great interest to many researchers. Up to now, most knowledge about cough has been collected through standardized questionnaires. Objective, and reliable detection of cough assessed by automated lung sound monitoring are becoming increasingly important. The aim of this study is to validate the LEOSound lung sound monitor by using previously determined and investigated COPD datasets (1,2).

Methods

Based on multiple recordings of 48 patients with stable COPD II-IV, we validated the cough detection algorithm of LEOSound by using a contingency table. Sensitivity, specificity, positive and negative predictive values were used as quantitative measures.

Results

We found the overall accuracy to be 87.3% with sensitivity and specificity of 98.7% and 80.2%, respectively. Major reasons for midsections in descending order were throat cleaning, snoring and movement artifacts.

Conclusion

In comparison to other full-automated cough monitoring systems, the LEOSound performs the best in sensitivity, but shows slightly poor specificity. Misdetactions were mainly caused due to morphological similar noises and can be withdrawn while scanning through the recording manually.

Background

The acoustic symptom cough is defined as a characteristic explosive sound. The typical noise arises due to turbulence of the outflowing air, vibrations of the tissue and movement
of liquid through the respiratory tract. The volume of the sound depends on the airflow rate that is achieved while coughing, the density of respiratory air, and of the dimension of the airways. (3,4)

Cough as a major symptom of Chronic Obstructive Pulmonary Disease (COPD), one of the leading causes of death worldwide(5,6) and many other diseases(4) is of great interest to a variety of different research fields. Up to now, research in cough mostly relied on questionnaires such as the Leicester Cough Questionnaire (LCQ)(7,8), Cough-specific quality of life questionnaire (CQLQ)(9) or in the case of COPD the COPD Assessment Test (CAT). Over the last decade, systems that record and automatically detect cough have been developed and used by several research groups. Such systems have enabled researchers and physicians to objectively analyze the symptom cough, which might be showing more different aspects of cough, compared to the subjectively assessed information by questionnaires (10). Consequently, the European Respiratory Society, as well as other cough researchers have recommended to consider both subjective and objective measures in the field of cough research(4,11). For the objective evaluation of cough measurement equipment is necessary

Currently available cough monitors include e.g. the Leicester Cough Monitor (LCM)(12), VitaloJAK(13), the Hull automated cough counter (HACC)(14) and the LEOSound Lung-Sound-Monitor(15). LEOSound was used in a variety of works addressing multiple acute and chronic diseases in different patient groups (1,2,16,17). Even though, LEOSound has been validated before in smaller settings in children(18), we would evaluate the embedded cough detection algorithm utilizing a larger cohort with chronic disease. In this regard, the LEOSound cough detection algorithm is validated in a cohort of stable COPD patients.

Methods
LEOSound Lung-Sound-Monitor

The LEOSound Lung-Sound-Monitor (Löwenstein Medical GmbH & Co. KG, Bad Ems, Germany) is a certified medical device with the purpose of lung sound monitoring during nighttime. The device ships with a software called Lung-Sound-Analyzer, which includes the display and replay functions, as well as the detection algorithms for cough and wheezing. In its default setting, LEOSound is applied using three bioacoustics sensors attached to the neck and back of the patient (see Fig 1). Additionally the system includes an ambient sound microphone fixed into the body of the LEOSound to distinguish between patient generated and external noises.(15) LEOSound is established in therapy monitoring in clinical trials and is used by established paediatricians, pneumologists and in sleep medicine (16,17).

Dataset

We have used a COPD dataset, familiar to the authors (1,2) for the purpose of this validation study. All recordings were acquired in an outpatient environment. The dataset consists of data from two consecutive nights from 48 different stable COPD patients, resulting in 96 recordings. The recordings started about 1–2 hours before patients usually go to bed and lasted approx. 10 hours in average. All three bioacoustics sensors of the LEOSound were applied at default positions on the neck and back of the patients (see Fig. 1). An overview of the demographics of the used dataset can be found in table 1.

Validation and statistics

LEOSound recordings are recorded in 30-second time segments, which we used as the basis of our validation. Medical experts scanned through every segment and assigned those to one of the categories of a contingency table. Rating was performed by using a self-implemented rating tool (implemented in MATLAB R2015b). Afterwards we pooled the
ratings together to calculate the classification parameters (i.) accuracy, (ii.) sensitivity, (iii.) specificity, and (iv.) positive and negative predictive values as objective measures of the tested algorithm. Due to a largely unbalanced dataset, we randomly selected a similar amount of cough containing and non-cough containing segments to increase the accuracy of our objective measures. We further analysed false positive detections to identify typical sound patterns, which could lead to misdetections.

Results

In total, our dataset included 1272 cough containing segments. Therefore, we randomly selected non-cough containing segments to roughly match the number of positive segments. The resulting contingency table is shown in table 2. Based on this contingency table we calculated the overall accuracy to be 87.3 %. Sensitivity and specificity are at 98.7 % and 80.2 % respectively. The PPV of the algorithm is 75.6 %, while the NPV is 99.0 %.

After further investigation of the false positive detections, we assigned those misdetections to categories of noises causing these. The major categories for misdetections in our dataset were the following: 29.7 % throat cleaning, 20.2 % snoring, 15.8 % movement artifacts, and 13.9 % moaning. The distribution of categories causing misdetections is illustrated in figure 2.

Multiple examples of the detection results are displayed in figures 3–6, including movement artifacts (fig 5) and snoring (fig 6).

Discussion And Conclusion

Sensitivity and specificity of the LEOSound Lung Sound Monitor are showing an accurate and sufficient detection performance of the introduced algorithm. PPV and NPV depict the tendency of overshooting the actual amount cough. As shown by the analysis of false
positive results, throat cleaning is the major reason for misdetections. However, throat cleaning, also referred to as harrumph or slight cough, is fulfilling a similar purpose as cough, while also sharing the same signal pathway with cough, and can be a sign for secretions in the upper airways (19). Therefore, we think it is up to debate whether throat cleaning misdetections should be treated the same way as the other categories like snoring. Depending on the diagnosis or hypothesis in question, physicians can decide whether throat cleaning is a useful parameter in their respective case. Other reasons for false positive results in decreasing order were snoring, movement artifacts and moaning. Movement artifacts are usually recorded as sudden rises of the amplitude, probably caused by scratching on the backside of the microphones. Those spikes in amplitude are similar to those caused by cough, but according to our analysis should be shorter. We think the algorithm in LEOSound can be improved by looking for length of a higher amplitude, rather than just for a sudden increase. Snoring can also incorporate sudden amplitude spikes, but has a different frequency pattern due to its harmonic properties (20). Therefore, spectral features can be used to distinguish cough and snoring. For moaning similar solutions might be applicable.

In comparison to other available cough detection devices and algorithms, it is evident that the LEOSound cough detection achieves a better sensitivity than all other validated devices, except for the VitaloJAK system. However, a comparison to the VitaloJAK system is difficult, since it is only a semi-automated cough detection device(21), whereas LEOSound is fully-automated. The main difference between VitaloJAK and LEOSound, or other fully-automated devices, is that the final counting of cough events for the VitaloJAK system is done by a rater, rather than an algorithm (7,22). Thus, data with reasonable sensitivity can be delivered with significantly less time and personnel expenditure in LEOSound. When compared to the LCM the LEOSound algorithm outperforms its sensitivity
by 13 % (85.7 % compared to 98.7 %), while also underperforming by 19 % (99.9 % compared to 80.3 %) in terms of specificity. Additional refinements of the detection results are necessary in both devices (7). The used dataset in the LCM validation is comparable to our dataset, but involves a more heterogeneous patient collective (12). Comparisons to the HACC are also difficult, because the HACC is only an algorithm, which requires an one channel audio input(14). Since the LEOSound algorithm has a tendency to overshoot the actual amount of coughing, comparisons with the HACC lead to similar conclusions as the comparison to LCM. The HACC is better in distinguishing cough from other noises, but is less effective in detecting cough. Also the validation dataset of the HACC research group is much smaller in recording time and number of patients included(14). Overall, we conclude that the LEOSound is having another approach with trying to achieve a maximum sensitivity, while others try to maximize their detection specificity. Therefore, no cough events are missed, while the false positive results can be further improved. Considering the uncommon use of cough detection devices in daily healthcare practice, one could assume that such rare recording would be validated by medical experts anyways. Assuming this, a quick dismiss of false positive results would be more manageable than scanning through the whole recording for potentially missed cough events or episodes.

List Of Abbreviations

CAT—COPD Assessment Test
COPD—Chronic Obstructive Pulmonary Disease
CQLQ—Cough-specific quality of life questionnaire
ERS—European Respiratory Society
FEV1—Forced expiratory volume after 1 sec
HACC—Hull-automated cough counter
LCQ—Leicester Cough Questionnaire

LCM—Leicester Cough Monitor

NPV—negative predictive value

PPV—positive predictive value

Declarations

Ethics approval and consent to participate

The study protocol was approved by the ethics committee of the University of Marburg (ref. 143/15) and written informed consent was obtained in all cases.

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available due to privacy concerns, because of sound recordings but are available from the corresponding author on reasonable request.

Competing interests

U. Koehler is affiliated with Löwenstein Medical GmbH & Co. KG, IfM, GlaxoSmithKline, Resmed, UCB Pharma, Boehringer Ingelheim, and Sanofi. V. Gross, P. Fischer, A. Weissflog are affiliated with Sanofi. The other authors have no conflicts of interest in this work to disclose.

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Authors’ contributions

V. Gross designed the concept of the article, developed the detection algorithm, analyzed the data and critically evaluated the manuscript. He approved the final manuscript as
submitted.

P. Fischer designed the concept of the article developed the detection algorithm, analyzed the data and critically evaluated the manuscript. He approved the final manuscript as submitted.

U. Koehler provided the study data, analyzed the data and critically evaluated the manuscript. He approved the final manuscript as submitted.

O. Hildebrandt provided the study data, analyzed the data and critically evaluated the manuscript. He approved the final manuscript as submitted.

A. Weissflog analyzed the data and critically evaluated the manuscript. He approved the final manuscript as submitted.

K. Sohrabi designed the concept of the article developed the detection algorithm, analyzed the data and critically evaluated the manuscript. He approved the final manuscript as submitted.

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Tables

Table 1 Demographics, baseline characteristics and lung function of the dataset. Displayed as mean +/- SD

| Demographic                  | COPD II-IV (n = 48) |
|------------------------------|---------------------|
| Age (years)                  | 67.1 ± 7.7          |
| BMI (kg/m2)                  | 26.3 ± 6.0          |
| Pack-years                   | 42.2 ± 20.9         |
| Male to female ratio         | 30:18               |
| FEV1 (% predicted)           | 46.2 ± 15.5         |

Abbreviations: BMI, Body-Mass-Index; kg, kilograms; m, meters; FEV1, forced expiratory volume after 1 second

Table 2 Contingency table for comparison of rater and algorithm based on a randomly sampled subset

|                | Rater |       |       |
|----------------|-------|-------|-------|
|                | right | false |       |
| Algorithm      | positive | 1255 | 17     |
|                | negative | 1644 | 406    |

Figures
Figure 1
LEOSound recorder with connected trachea microphone (left) and two lung microphones (right)
Figure 2

Categories for causing midsections of the cough detection algorithm in our dataset
Figure 3

Screenshot from LEOSound Lung-Sound-Analyzer Software, showing an overview on the top and the spectrograms of a 30-second time segment in the lower part. Depicted are 3 cough events in the end, marked in green (Patient ID: 31, Night: 1)
Figure 4

Screenshot from LEOSound Lung-Sound-Analyzer Software, showing a cough epochs, consisting of 14 cough events, in the middle of the segment. Cough detection is marked in green (Patient ID: 14, Night: 1)
Figure 5

Screenshot of a 30 second time segment containing movement artifacts, which are falsely detected as cough. Cough detection is marked in green (Patient ID: 14, Night: 1)
Figure 6

30-second time segment containing false positive cough detection, marked in green. The detected events are snoring events, indicated by the harmonics in the spectrogram. (Patient ID: 14, Night: 1)