Detection of different types of noise in lung sounds

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***Abstract*— Lung sound signal processing has proven to be a great improvement to the traditional acoustic interpretation of lung sounds. However, that analysis can be seriously hindered by the presence of different types of noise originated in the acquisition environment or caused by physiological processes. Consequently, the diagnostic accuracy of pulmonary diseases can be severely affected, especially if the implementation of telemonitoring systems is considered. The present study is focused on the implementation of an algorithm able to identify noisy periods, either voluntarily (vocalizations, chest movement and background voices) or involuntarily produced during acquisitions of lung sounds. The developed approach also had to deal with the presence of simulated cough events, that carry important diagnostic information regarding several pulmonary diseases. Features such as Katz fractal dimension, Teager-Kaiser energy operator and normalized mutual information, were extracted from the time domain of healthy and a pathological lung signals. Noise detection was the result of a good discrimination between uncontaminated lung sounds and both cough and noise episodes and a slightly worse classification of cough events. In fact, detection of cough periods carrying diagnostic information was influenced by the presence of two other types of noise having similar signal characteristics.**

I. Introduction

Auscultation of lung sounds (LSs) is a low-cost, practical and non-invasive technique, therefore very useful in early diagnosis and further monitoring of pulmonary diseases. Additionally, auscultation performed with electronic stethoscopes has proved to be an important asset which complements the physician's interpretation of the auditory information. In fact, the identification of abnormal acoustic respiratory sounds is highly dependent on the physician performing auscultation and has then been drastically improved by using digital signal processing methods to analyse those LSs. Telemonitoring p-health systems also rely on sensors, namely microphones, integrated on wearable vests for long-term home-based monitoring. Those systems have been shown to be particularly important in detection and monitoring of chronic diseases, namely chronic obstructive pulmonary diseases (COPDs) [1], [2]. The incidence of this disease has been foretold to increase in the next years and soon became the third worldwide leading cause of death. This disease is common in older adults and is characterized by the presence of adventitious LSs along the normal breathing cycle, such as wheezes and crackles [2]. Furthermore, COPD is often associated with dyspnea, chronic cough and sputum production [3].

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LS auscultation in non-controlled environments such as busy clinics or at home can be hampered by different surrounding interferences including background voices, music, objects' handling, etc. Furthermore, lung signals can also be contaminated with noise produced by internal sources such as movement of the chest, subject's voice, heart sounds, stomach growls, intestinal and breathing sounds, among others. Consequently, acquisition of lung signals in unpredictable noisy environments requires the development of algorithms able to detect events of noise and reduce its impact on the further analysis regarding the detection of disease.

In the last fifteen years, few studies have been released reporting algorithms designed for identification and/or cancellation of different noise types contaminating LSs that have been acquired in non-ideal noisy settings. Emmanouilidou & Elhilali [4] analysed LSs recorded in the presence of different types of noise. Features were extracted from the frequency spectrum (peak width, spectrum slope, power ratio, low-to-high frequency ratio and harmonicity) and submitted to classification using support vector machines. Average accuracy was above 91% for clean LSs, background voice and stethoscope movement type of noises and 85% for LSs contaminated with electronic interferences. However, each type of noise was present in individual signals of 0.3-3 seconds. Additionally, two types of signal were predominantly analysed: LS clips free from noise or contaminated with background noise.

Spectral subtraction has also been widely used to suppress noise from lung sounds. Towards that, an external sensor is usually used to record exclusively surrounding noise during LSs acquisitions [5], [6] or, alternatively, a noise estimate can be obtained while the subject is sustaining breath [7].

The purpose of the present study is therefore the detection of noisy segments introduced along the lung signals. Afterwards, the uncontaminated LSs contain diagnostic information can be accurately assessed as to the presence of abnormal LSs.Assuming the acquisition of long-term lung signals in non-controlled home-based facilities (home screening), it is expected to have a great amount of data available for analysis. Accordingly, the developed algorithm addresses the identification of the noise periods, with no need for a cancellation procedure.

II. Material and Methods

A. Data Collection

In this study LSs from two different datasets underwent analysis. Data were acquired when subjects were in a sitting

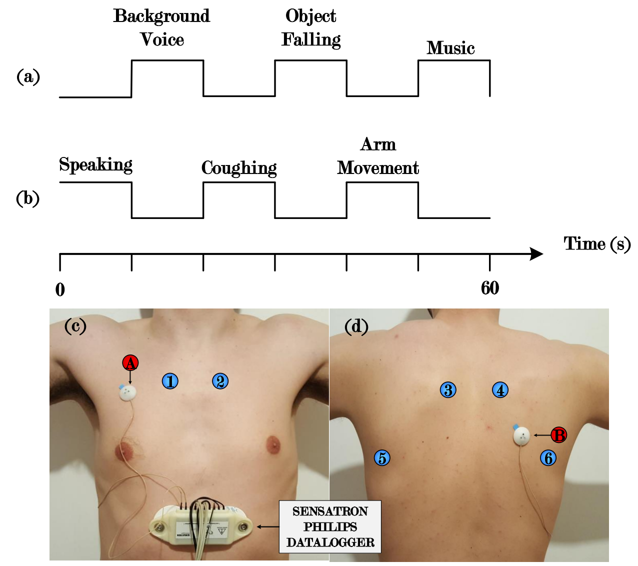

Fig. 1: Lung sound acquisition protocol for the healthy dataset having (a) external (task 1) and (b) internal (task 2) interferences. Lung signals were recorded in (c) anterior and (d) posterior chest, with the numbers and the letters referring to the healthy and pathological dataset auscultation sites, respectively.

position. Lung signals last on average 60 seconds.

One of the datasets includes 20 healthy volunteers which agreed with data acquisition and processing under anonymous conditions. A protocol was followed during acquisitions in which different types of noise were deliberately introduced either by an external source or by the subject participating in the study (see Fig. 1). Subjects were asked to perform two runs of two distinct tasks. In addition to those noisy periods willingly produced during acquisitions, other unpredictable interferences could be heard along the signals and have also been annotated. Two microphones integrated in Philips Sensatron data-logger (sampling rate of 4000 Hz) were attached to different auscultation positions in the chest (see Fig. 1, positions A and B).

Lung sounds were also recorded in a pathological population at the George Papanikolaou General Hospital of Thessaloniki, in Greece. The Ethical Committee of the hospital authorized the acquisition of the data. The seven participants comprising this pathological dataset were diagnosed with COPD. During acquisitions, patients were asked to cough and speak (namely, count from one to ten). Additionally, interferences such as hair rub and speech and cough in the background also occurred. All those events were annotated by the physicians who supervised the acquisition. Cough and speech periods last on average 5-6 seconds. A single stethoscope 3M Littman 3200 (sampling rate of 10000 Hz) was used to record the lung signals in six different auscultation sites (see Fig. 1, positions 1 to 6). These signals were downsampled to 4000 Hz.

B. Method

An algorithm was implemented in order to accurately detect noisy segments in lung sounds. In other words, the developed methodology should be able to identify the periods when subjects are speaking or moving as well as periods of signal affected by the surrounding interferences occurring during acquisitions. The events of cough, however, can not be considered noise as that is a common symptom of several pulmonary diseases such as pulmonary fibrosis, COPD and lung cancer. As result, cough can be used as a screening feature in clinical practice and will then be considered as a distinct class in this study.

Therefore, a simple three step rationale was designed to classify the three different classes: (i) speech and other noises, (ii) cough and (iii) clean lung sounds. The first step consists in the discrimination between all occurring events (including cough, speech and other types of noise) and clean lung sounds and is followed by a second step aiming to detect only the presence of cough along the respiratory signals. The third and last stage corresponds to the classification of the noisy events (including speech) using the output of the two previous classifications (see Fig. 2).

More specifically, a binary classification is performed in each step using the respective extracted features, described in detail below. A vector of 0's (class 1) and 1's (class 2), herein called *detected*, is obtained in the end of the classification. Then, with the information about the location of the events of cough, speech and other interferences, *detected1*, and the identification of the cough periods, *detected2*, it is possible to detect the segments of noise resorting to logical operations (see Fig. 2). The binary *detected* vector is obtained by using a linear classifier which in turn requires the definition of a threshold, specific for each feature. For example, if the value of a given feature in a given window is above a fixed threshold, that window is classified as contaminated.

The best window and overlap used to span the signals and also the best threshold that maximizes the discrimination between two classes were defined in the training phase of the classification. Having the annotations of the events happening along acquisitions and extracting features from a training dataset it was possible to obtain the parameters corresponding to the optimal performance of the algorithm.

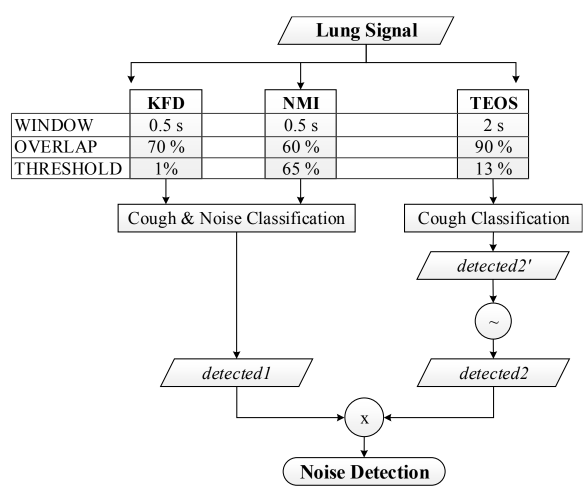

Fig. 2: Multi-stage algorithm for the detection of noise.

Towards that, combinations of differently sized and overlapped windows and also different thresholds were tested. Taking into account that the minimum duration of the noisy periods occurring in the signal corresponds to approximately one second, 0.5, 1 and 2 second windows and 60, 70, 80 and 90 % of window overlap were tested. A total of 100 thresholds, ranging from the minimum to the maximum of the feature's amplitude were also tried. These thresholds were defined to be a percentage of the signal's amplitude, introducing adaptivity regarding different types of events and also different datasets, gathered using specific sensors. Sensitivity (SE) and specificity (SP) values were obtained for each combination of the mentioned parameters, being depicted in a ROC curve. The parameters corresponding to the values of SE and SP that maximize the curve were then introduced in the final algorithm which was validated using a testing dataset (see Fig. 2).

The data acquired during performance of task 2 in the healthy dataset (20 subjects) was used in the training phase. During task 1, however, subjects were not asked to simulate cough hence being only possible to compute specificity values. Therefore, the task 1 data were used to validate the algorithm, as well as the pathological dataset (seven subjects).

Finally, depending on the events to be classified, different features were computed and are briefly described bellow. Namely, detection of cough and noise was performed resorting to the feature Katz fractal dimension (KFD) and normalized mutual information (NMI) and detection of cough events, on the other side, involved the computation of Teager-Kaiser energy operator (TEO).

1) Teager-Kaiser energy operator sum (TEOS): The Teager-Kaiser non-linear energy operator makes possible to enhance abrupt discontinuities both in time and frequency domains and simultaneously minimize smooth transitions occurring in the signal [8].

The feature, TEOS, is computed by summing the discrete TEO in a given window w with N samples (see 1).

$$TEOS^{w} = \sum_{n=2}^{N-1} \Big((x_w[n])^2 + x_w[n-1]x_w[n+1] \Big) \quad (1)$$

2) Katz fractal dimension: This feature measures the complexity of a given signal in the time domain. It depends on the sum of the Euclidean distance between successive points (L), on the distance between the first point of the window and the point of the window at which the distance is maximal (d) and on the number of steps in the window $n = N - 1$, where N is the length of the input data (see 2) [9], [10].

$$KFD = \frac{\log_{10}(n)}{\log_{10}\left(\frac{d}{L}\right) + \log_{10}(n)} \quad (2)$$

3) Normalized mutual information (NMI): This feature is given by the normalized mutual information between a screened free noise window (X) called *reference* window, and the other windows (Y) named *test* windows into which the lung signal was divided.

$$NMI = \frac{H(X) + H(Y) - H(X,Y)}{H(X)} \quad (3)$$

NMI provides information about the statistical dependence between two variables. In this case NMI is computed using the entropies of the *reference* ($H(X)$) and *test* ($H(Y)$) windows and its corresponding joint entropy $H(X,Y)$. The *reference* window corresponds to the window in the signal with the lowest value of TEO.

All calculus were performed in Matlab R2015a on Windows 10 using an Intel® Core™i7-4790K CPU at 4GHz.

III. Results and Discussion

The results of classification are presented in Tables I and II and correspond to the average of sensitivity and specificity for all participants. Concerning the pathological dataset, it should be noticed that an algorithm that raises less false positives has priority over another one returning less false negatives. In other words, a high specificity means that the algorithm strictly detected noisy events rather than pathological lung sounds, decreasing the impact of noise in the diagnostic. Furthermore, it must also be highlighted that in the pathological dataset, the lung signals corresponding to different auscultation sites had not been acquired simultaneously. Therefore, each signal was affected by different types of non-controlled noise and the task was performed slightly different in every chest location, introducing variability among auscultation sites.

The detection of cough events in the training dataset resulted in an higher sensitivity than specificity, which can be partly explained by the ratio between duration of the cough events and the size of the entire lung signal (approximately 1/6). Additionally, blocks during which subjects had to perform chest movements in task 2 and blocks during which an object fell in task 1 were classified as cough in a few signals. Besides those events' duration being on average 10 seconds (see Fig. 1), they are sometimes over-simulated turning into a non-realist interference in the signal. In fact, there are signals presenting higher amplitude episodes of chest movement and object falling comparing to cough, either in time domain or in the frequency spectrum, making it hard to find a robust feature, amplitude independent, to use specifically for cough detection.

On the other hand, sensitivity can be affected by the annotation of each event. For instance, sometimes three sequential cough simulations were annotated as a block and the algorithm identified them as individual events instead of blocks, thus counting for the false negatives and decreasing sensitivity values. To assess the impact of the annotation factor, the events from the healthy training dataset were annotated as individual occurrences and data was classified

TABLE I: Classification results for the healthy dataset.

Task	Testing: Task 1						Training: Task 2					
Event	Cough		Cough & Noise		Noise		Cough		Cough & Noise		Noise	
Parameter	SE	SP	SE	SP	SE	SP	SE	SP	SE	SP	SE	SP
Channel A	-	76.22	95.06	91.57	52.78	93.89	99.09	92.04	89.53	93.23	68.58	81.17
Channel B	-	80.85	89.54	94.53	51.85	96.23	96.39	92.46	89.69	95.34	75.99	85.21
Average	-	78.54	92.30	93.05	52.32	95.06	97.74	92.25	89.61	94.28	72.29	84.69

for the two options, returning better results for the block annotations.

Despite the aforementioned reasons, the detection of cough and noise was satisfactorily accomplished in both testing and training healthy datasets. In pathological dataset, however results were far worse that expected. In fact, this classification is mainly limited by the already mentioned detection of false negatives resulting from the comparison of the block type of annotation with the *detected* vector comprising individual noisy events.

With regard to the classification of noise, sensitivity and specificity values reflect the impact of the misclassification of cough events, with a drastic decrease in the values of sensitivity comparing to specificity. Classification of cough and noise, even though with better results will also influence the final noise detection.

The use of different sensors may also explain the variability of the obtained results, across datasets. The signal morphology varies from sensor to sensor and even more from a microphone to a digital stethoscope. In fact, handling a stethoscope can cause unpredictable abrasion artifacts, which include excessive pressure on the patient or slight movements with the stethoscope chestpiece. That type of noise is typically reduced when using microphones, as they are attached to the chest and therefore remain more steady.

IV. Conclusions

New lung sound denoising methodologies are required when acquisitions occur in non-controlled conditions, either at busy hospital facilities or at home, while making use of telemonitoring systems. In fact, there is a lack of suitable algorithms to detect the presence of noisy events in lung signals including for example vocalizations and/or interferences from the acquisition environment. Those algorithms should however be able to identify cough periods as not being a type of noise but instead as a diagnostic indicator of the presence of pulmonary diseases. In this study attempts were made in order to solely detect all annotated noisy events rather than cough events. The developed algorithm successfully distinguished cough from the different types of noise with exception of chest movement and object falling long duration blocks of interferences. Nevertheless, the study shed light on new ways to deal with the presence of different types of noise in lung signals. Future work includes the acquisition of more lung signals, both healthy and pathological, using microphones and also the development of multi-class approach.

TABLE II: Classification results for the pathological testing dataset.

Event	Cough		Cough & Noise		Noise	
Parameter	SE	SP	SE	SP	SE	SP
Channel 1	90.50	83.18	59.09	91.80	10.77	87.91
Channel 2	75.81	82.89	71.99	88.39	19.77	84.57
Channel 3	73.59	81.93	67.72	92.20	24.23	88.14
Channel 4	79.53	86.36	63.54	87.79	25.60	83.74
Channel 5	75.35	81.38	72.85	69.89	37.48	71.15
Channel 6	85.43	77.38	79.04	62.09	37.87	72.40
Average	80.15	82.15	69.04	82.03	26.63	81.32

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