

# Sensor-based System for Automatic Cough Detection and Classification

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**Abstract.** Cough detection and classification present necessary tools for the evaluation of pathology severity in chronic illnesses. In literature, several approaches have been proposed for this aim. The latter presented a relative success since none of them allow a standardized exploitation and interpretation of sensors results in order to provide an efficient cough detection and classification. This paper presents a new system that disposes of a prototype (hardware) for data acquisition, and software for exploiting the acquired data for cough detection, visualization and classification. Our prototype includes sensors such as ECG, thermistor, chest belt, accelerometer, oximeter, contact and audio microphones. The relevance of each sensor is evaluated within three features: mutual information obtained with the features, ability to distinguish cough from other event categories, and ability to detect cough events. The sensors values are interpreted and visualized with a graphical view where the detected cough extracts are visualized and organized accordingly to their similarity in terms of audio properties such as timbre, cough duration and signal energy.

**Key words :** Biomedical Engineering, Sensor, Audio Processing, Cough Detection, Cough Classification.

## 1 Introduction

The general definition of cough can be presented by the sudden and involuntary expulsion of air from lungs with a harsh sound. Otherwise, for respiratory physiologists, cough is three-phase expulsive motor act characterized by an inspiratory effort, followed by a forced expiratory effort against a closed glottis and then by opening of the glottis and rapid expiratory airflow [1]. Cough presents also the common reason that makes patients asking medical advice to the general practitioner (around 20% of consultations for children below 4 years old), the pediatrician and the pulmonologist (for whom chronic cough represents one third of consultations [2]).

The impact of cough and particularly chronic coughing on life quality can be so significant. Therefore, the assessment and evaluation of cough severity

presents a high importance in clinical use. It requires a combination of measures characterizing cough frequency, duration, energy, intensity, and its impact on quality of life.

Actually, the assessment of cough severity is subjective since it is based on some values that are completed by the patient itself or a parent [3] [4]. The main used values are cough scores, diaries, visual analogue scales (VAS) and symptom questionnaires. In medical literature [5], the objective and subjective perception of cough severity are modestly correlated. Thus, a real need arose to develop a reliable tool to measure the severity of this symptom [1]. This kind of tool is also necessary to test the effectiveness of cough treatments (e.g. antitussives) or novel therapies.

In the context of automatic cough detection, several approaches have been proposed. Generally, they consist on coupling various sensors to the audio signal such as accelerometer, chest impedance belt, contact microphone, ECG, respiratory inductance plethysmography, etc. The related results are well encouraging but none of them offer standardized method or adequately validated, commercially available and clinically acceptable cough monitors [1].

Several challenges have to be faced with automatic cough monitors. First, cough should be differentiated from surrounding noise and other parasitic patient sounds (throat clearing, laughing, forced expiration, etc.). Secondly, the acoustic properties of coughs vary with individuals and diseases, but also within individuals. It is also preferred to monitor cough continuously for long periods (over 24h) and in the patient's own environment. Finally, the related information about detected coughs should be well visualized in a graphic view that allows a fast interpretation of results. Moreover, the detected cough should be classified with a graphic view in order to offer an efficient analysis of patient coughs within different moments with no need for listening all the detected cough.

The remainder of the paper is presented as follows: related works are presented in the second section. Section 3 describes the acquisition system, while section 4 presents the recorded database used to develop and evaluate the cough monitor. In section 5, we detail our cough detection algorithm. Section 6 is devoted to present the graphic view where the detected cough extracts are visualized and classified accordingly to their similarity in terms of audio properties such as timbre, cough duration and signal energy. The last section draws the conclusions of this study.

## 2 Related work

In literature, several cough monitors have been proposed [6]. The first one has been developed in 1950 with simple audio recording systems that enable to spot manually cough events. In the other hand, some semi or fully automated cough recorders have been designed. In 2006, the Hull Automated Cough Counter (*HACC*) [7] was developed. It consists of a single audio signal fed into an artificial neural network for detecting cough events. The number of cough components per event is not computed by the system, but can be manually determined. The

system presents a sensitivity of 80% (ranging from 55% to 100% across the 10 validation patients).

The Leicester Cough Monitor (*LCM*) [8] also relied on audio recordings only. Hidden Markov Models (HMM) are used to pre-segment possible cough events, achieving overall sensitivity and specificity of 91 and 99%, respectively. Another system called "The Vitalojak" [9] is based on a contact microphone placed on the thorax for a semi-automated detection. A lapel microphone is integrated in the system for manual validation. This system has been validated in a 24-hour ambulatory context on 10 patients [10]. It offers a sensitivity higher than 99% while compressing the amount of data to check manually with 3 possible levels, ranging from 65 to 23 minutes on average. In [11], we proposed an audio-only system based on artificial neural networks which achieved a sensitivity and specificity of about 95% on voluntary cough from 10 healthy subjects in various conditions. In [12], we analyzed in an objective way the performance of several sensors for cough detection: ECG, thermistor, chest belt, accelerometer, contact and audio microphones.

Our contribution consists on exploiting and improving our previously published [12] results within three main factors:

1. Optimization and acceleration of the process of data acquisition within a new prototype, by exploiting fast access memories. This allowed to store data quickly. Consequently, all data are well saved without audio interruptions and noise.
2. Improvement of cough detection precision by extracting cough events which can be presented with several close and successive coughs.
3. The sensors values are interpreted and visualized with a graphical view where the detected cough extracts are visualized and organized accordingly to their similarity in terms of audio properties such as timbre, cough duration and signal energy.

### 3 Acquisition System

The acquisition system enables to capture and store data from sensors. Signals are not analyzed or processed in this step, which is performed off-line. The block diagram of the acquisition system is displayed in Fig. 1. It is implemented as a classical acquisition system by means of sensors, analog signal conditioning circuit (front-end), analog-to-digital conversion, communication, and storing functional blocks. For more details about this acquisition system, we refer authors to [12]. Notice that this system has been improved since the new prototype integrates an oximeter sensor for measuring, simultaneously, the concentration of oxygen in the blood. However, the integration of this new sensor has induced the reduction of battery life and also some noise due to the slow storage of several sensors data. Therefore, we proposed to exploit fast access memory card for storing our data such as SD card class 10. Fig. 2 presents our prototype showing its main components (sensors).

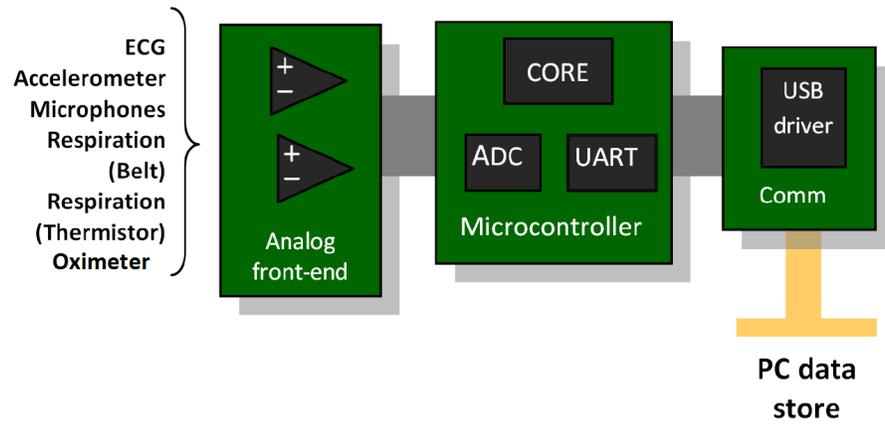


Fig. 1: Block diagram of the acquisition system.

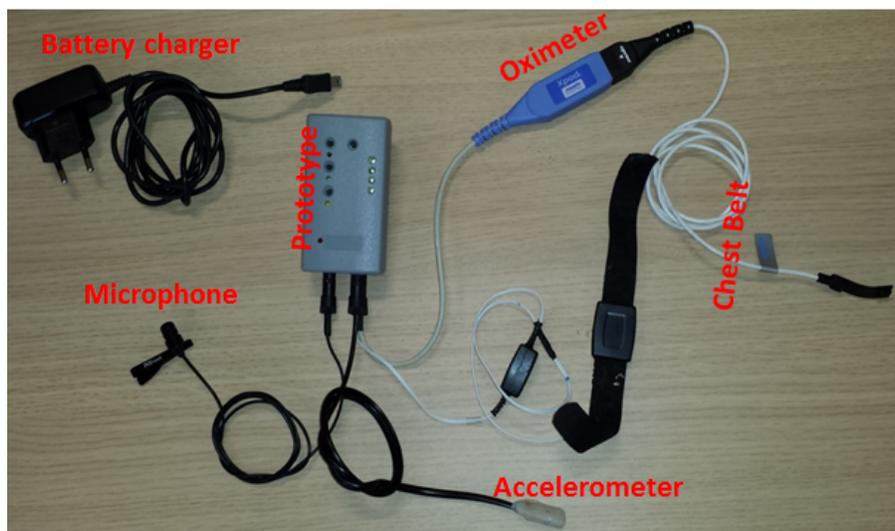


Fig. 2: Sensor-based Cough detection prototype.

## 4 Database

The study population that we used for our experiments is presented in two groups. The first set (A) included 22 healthy subjects (9 Male, mean age $\pm$ SD:  $22.8 \pm 2.44$ , range: 20 – 28). The second set (B), consisting of 10 additional healthy subjects (5 Male, mean age $\pm$ SD:  $23 \pm 1.45$ , range: 22 – 26) was designed to compare our system to the commercially available KarmelSonix cough counter [13].

Sounds	Situations		
	Sitting down, quiet environment (n)	Sitting down, noisy environment (n)	Climbing/going down a stepladder (n)
High volume cough	5	5	5
Interm. vol. cough	5	5	5
Low vol. cough	5	5	5
Fit of coughing	3	3	3
Forced expiration	3	3	3
Throat clearing	5	5	5
Speaking	14	14	14
Laughing	3	3	3

Table 1: *Standardized protocol for data recordings*

Our database is composed from various recorded cough sounds but also some other sounds which are typically confused with cough. The participants followed a standardized protocol performed in three different situations, as detailed in Table 1: (a) sitting down in a quiet environment, (b) sitting down in a noisy environment and (c) climbing on/going down of a stepladder.

All recordings have been precisely manually annotated by a trained observer. In total, the database contains 2338 coughs (among which 864 are from fits of coughing), 289 forced expirations, 479 throat clearings, 289 laughers, for a total duration of 237 minutes. Note that slight deviations were observed from the strict protocol, but that the manual annotation was made coherently.

## 5 Cough detection algorithm

The general workflow for the automatic detection of cough used through out this paper is displayed in Fig. 3. From the signals captured by a given sensor, or by several sensors in a multimodal approach, the first step aims at extracting a wide variety of features. Since this leads to a prohibitive number of features, a step of dimensionality reduction is necessary by selecting only the most relevant ones. This is here achieved based on some measures derived from the Information Theory. Finally, an Artificial Neural Network (ANN) based classifier is used for modeling, accurately, the feature distributions and for drawing the final

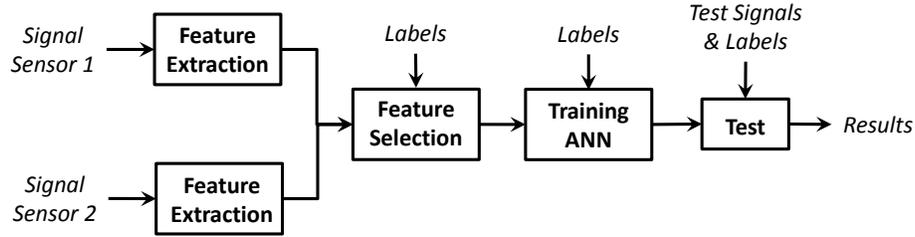


Fig. 3: Workflow used in this study for the automatic multimodal detection of cough.

cough detection decision. For more details about the proposed algorithm, we refer authors to [12].

The above-mentioned algorithm has been improved within the main factors:

1. Accurate cough duration: the above-mentioned algorithm allowed to detect coughs with a high precision. However, in several situations, the same cough was detected for twice (two coughs detected with the same end time). To overcome this constraint, we start by detecting repeated coughs by comparing the start and end times of each two consecutive coughs. Indeed, if two successive coughs present the same end time and two close start times, we consider one cough only by keeping the longest cough in terms of duration. Moreover, we compute the number of coughs per minute.
2. Cough event detection: this consists in comparing the time between each two successive coughs. For example, we compare the end time of the  $i^{th}$  cough with the start time of  $(i + 1)^{th}$  cough. If the difference value is lower than the threshold value, the both  $(i$  and  $(i + 1))$  are included in the same cough event. The threshold is defined by applying our algorithm on the above-mentioned data. As result, we obtain a mean threshold of 3 ms that could separate two cough events.

## 6 Cough classification and visualization

In order to interpret easily the obtained results which include the detected coughs, cough events, accelerometer and oximeter signals. We developed a GUI that offered a simultaneous presentation of the obtained results and signals, which allow doctors to perform an accurate diagnosis. Fig. 4 presents our GUI that visualizes the audio signal with the corresponding number of coughs, cough events, etc. Each detected cough is characterized by its duration and energy, which are presented with two graphs as presented in Fig. 4. The audio, Heart Rate (HR), Oxygen Saturation (SpO2) and accelerometer signal are displayed with the same interface in order to provide a complete information about patients. Notice that Oxygen saturation (SpO2) signal is obtained from the oximeter using a C++ program that allowed to decode the captured signal.

Once the results are displayed, the detected coughs are saved (in .wav format) in the project directory (that could be changed by users). These cough extracts

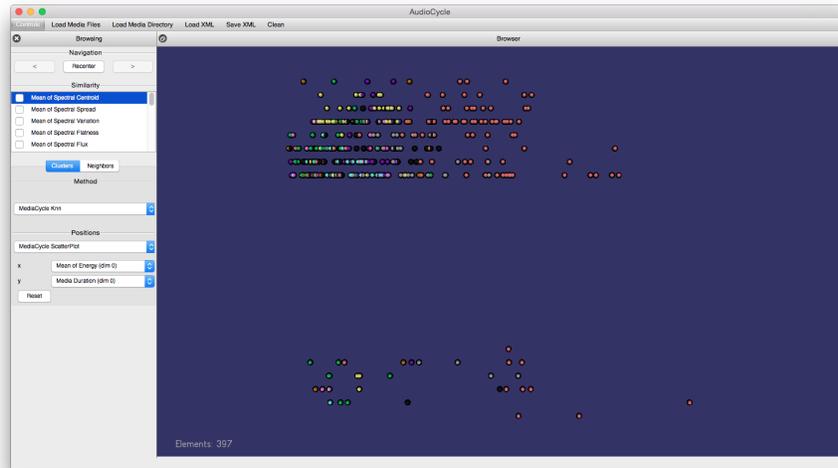


Fig. 4: *Sensor-based Interface for Automatic Cough Detection.*

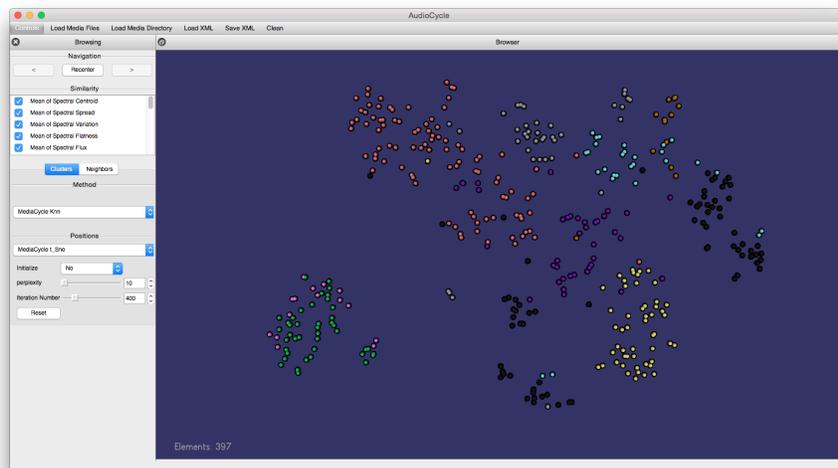
are then classified within the AudioCycle prototype application [14] used initially for browsing through music loop libraries. It offers a graphical view where the audio extracts are visualized and organized according to their similarity in terms of musical properties, such as timbre, harmony, and rhythm. In our case, the cough extracts are organized and classified according to their similarity in terms of cough timbres, durations and energies. Fig. 5a illustrates the classification of detected coughs from 10 patients. Each patient is represented by a distinct color, while the coughs are classified in terms of their timbres and energies. Notice that the user can apply for a classification in terms of cough energies and durations as shown in Fig. 5b.

The experimental results can be described in two parts. On the one hand, the various features for each sensor are first evaluated based on their mutual information with the classes, i.e. on their discrimination power for detecting cough. This study is well detailed in our previous publication [12]. The oximeter sensor has been integrated within the new version in order to provide the oxygen saturation information (SpO<sub>2</sub>). This allows to observe the influence of coughs on oxygen saturation.

In the other hand, the accuracy of the proposed approach remains identical to our previous publication showing an averaged sensitivity of 94.7 %. However, the new version allows a better precision since close extracts of coughs are well separated, which allows to perform a robust diagnosis. Moreover, we improved the detection by extracting cough events. The latter indicates the presence of



(a) Classification in terms of cough durations and energies



(b) Classification in terms of cough timbres and durations

Fig. 5: Classification of coughs accordingly to their similarity

successive coughs which present relevant information for the diagnosis. Notice also that the new system provides a classification of the detected coughs based on computing their similarity in terms of cough timbre, energy and duration. A graphic view (GUI) is proposed in order to offer a simple and easier interpretation and visualization of results.

## 7 Conclusion

We proposed in this paper a new system that allows to detect and compute coughs using several sensors: ECG, thermistor, chest belt, oximeter, accelerometer, contact and audio microphones. Based on the captured values from these sensors, we applied feature extraction and classification algorithms for detecting coughs, which offered an averaged sensitivity of 94.7 %. Our system allows also to extract cough events which can be defined as a group of close and successive coughs. Otherwise, the obtained results are interpreted and visualized with a graphical view (GUI) where the detected cough extracts are visualized and organized accordingly to their similarity in terms of audio properties such as timbre, cough duration and signal energy. As future work, we plan to encompass the validation of our prototype in patients with cystic fibrosis. We plan also to accelerate the process of cough detection by exploiting parallel (GPU) [15] and heterogeneous (Multi-CPU/Multi-GPU) [16] platforms.

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