Detection of Cough Signals in Continuous Audio Recordings Using Hidden Markov Models

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***Abstract*—Cough is a common symptom of many respiratory diseases. The evaluation of its intensity and frequency of occurrence could provide valuable clinical information in the assessment of patients with chronic cough. In this paper we propose the use of hidden Markov models (HMMs) to automatically detect cough sounds from continuous ambulatory recordings. The recording system consists of a digital sound recorder and a microphone attached to the patient's chest. The recognition algorithm follows a keyword-spotting approach, with cough sounds representing the keywords. It was trained on 821 min selected from 10 ambulatory recordings, including 2473 manually labeled cough events, and tested on a database of nine recordings from separate patients with a total recording time of 3060 min and comprising 2155 cough events. The average detection rate was 82% at a false alarm rate of seven events/h, when considering only events above an energy threshold relative to each recording's average energy. These results suggest that HMMs can be applied to the detection of cough sounds from ambulatory patients. A postprocessing stage to perform a more detailed analysis on the detected events is under development, and could allow the rejection of some of the incorrectly detected events.**

***Index Terms*—Automatic detection, cough counts, cough monitor, hidden Markov models.**

I. Introduction

COUGH is a normal protective reflex which clears the respiratory tract and prevents the entrance of noxious materials into the respiratory system. Cough is not frequent in healthy subjects, but it is a common symptom of many respiratory diseases, including asthma, gastro-oesophageal reflux (GOR), postnasal drip, bronchiectasis and chronic bronchitis [1], [2].

A reliable measure of cough is needed so that the severity of cough in a particular patient and the effectiveness of treatment can be assessed. This evaluation of cough severity has so far relied mainly on subjective measures, such as cough reflex sensitivity, and on the patient's perception of the symptom, assessed by cough visual analogue scores, quality of life questionnaires, cough symptom scores and patient's diaries [1]. The subjectivity and lack of robustness of these tests have led to increased interest in developing automated ambulatory cough monitors as an objective method of measuring the frequency and intensity of cough in patients suffering from chronic cough, which could be used as a measure of cough severity.

The basic requirements for an automatic cough monitor are the possibility to record over a representative amount of time using a portable recording system and the capacity to automatically detect the occurrences of cough sounds from the recordings using a specially designed algorithm.

Some systems have been proposed for ambulatory cough monitoring, allowing up to 24 h of recording, but they still rely on human experts to manually analyze the recordings and select the occurrences of cough sounds [3]–[5]. Two of these systems record signals both from a microphone and electromyography (EMG) electrodes, using low sampling frequencies. The recorded data is analyzed with the help of a personal computer, and patterns in the audio and EMG signals that correspond to cough sounds are counted [3], [5]. The system described in [4] uses audio signals sampled at 8 kHz. Data reduction is achieved by selecting 1-s segments that contain signal above an energy threshold. The selected segments of recording are then played back for identification of cough sounds.

The manual examination of cough monitoring recordings is a slow and tedious process, which makes the general use of cough monitors in clinical practice difficult. A reliable cough detection algorithm could reduce the amount of data to be manually analyzed or even eliminate the need for manual analysis, thus improving the usefulness of cough monitors. This requires an algorithm capable of detecting the majority of cough sounds present in a given recording, while rejecting other sounds that can have similar characteristics to cough sounds.

The two main difficulties in developing such an algorithm are the variability of the cough sounds between different subjects and the occurrence of similar sounds in the recordings that can be taken by the algorithm as being cough sounds, for example throat clearing, speech, sneezing, laughing and other ambient sounds. The first aspect can lower the sensitivity of the algorithm for a particular recording, due to the lack of generalization of the algorithm to the type of cough sounds present in that recording, and the second aspect can lower its specificity, due to the occurrence of events incorrectly detected as cough events.

Fig. 1 shows examples of cough sounds obtained from three different patients. It can be seen that the signals obtained can vary substantially from patient to patient. Fig. 2 shows examples of sounds that can generate false alarm (FA) events in the algorithm's result. The signal in Fig. 2(a). corresponds to a "throat

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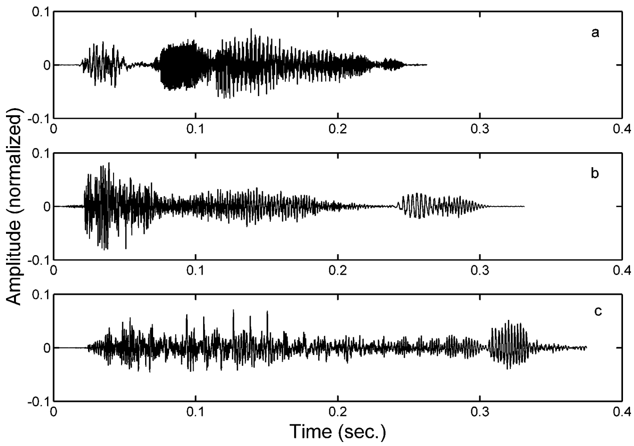

Fig. 1. Cough sound examples, obtained from three different patients.

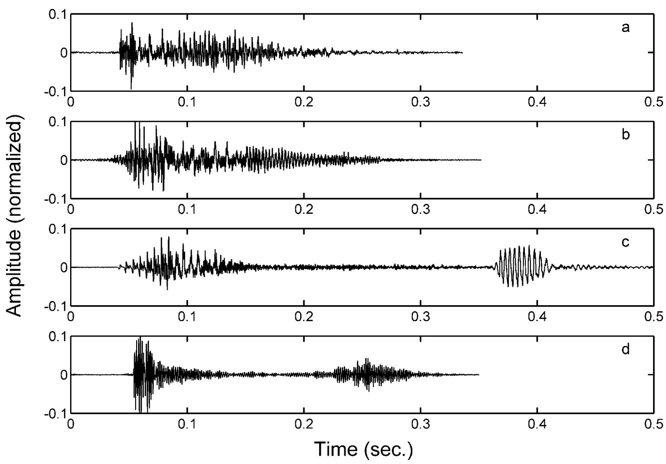

Fig. 2. Example sounds obtained from continuous recordings: (a) throat clearing; (b) sneeze, (c) laughter, (d) impulsive noise.

clearing" sound, the one in Fig. 2(b). corresponds to a sneeze and the one in Fig. 2(c). is a segment of laughter. The transient signal shown in Fig. 2(d). corresponds to an impulsive noise recorded by the microphone.

As can be seen from Fig. 1, cough sounds exhibit a time varying structure that defines each sound's characteristics. To allow the detection of such signals and the differentiation from other recorded sounds, these time varying characteristics should be used. In this study, we use hidden Markov models (HMMs) to represent the time varying characteristics of cough sounds. The HMM is a statistical method used for characterizing the spectral properties of a signal, which has been mainly used in speech recognition systems because of its ability to represent the variability and time varying nature of the signals encountered [6], [7].

We propose a keyword-spotting approach, based on HMMs, to detect cough events from continuous ambulatory recordings from patients with different respiratory conditions. The idea in keyword-spotting is to detect occurrences of keywords in a continuous speech recording [8]. In HMM-based keyword-spotting, only the patterns representing the keywords in which we are interested are modeled by specific models, while more general

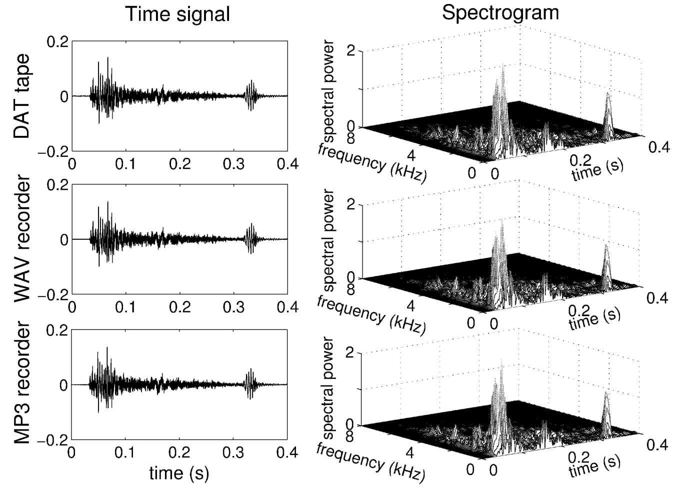

Fig. 3. Example voluntary cough sound recorded by three different recorders.

models, usually called "filler" models, are used to represent the rest of the data. In our implementation, we are interested in detecting "cough" sounds from continuous data, and we create statistical models to represent these patterns and detect their occurrence from the output of a recognizer.

II. Methods

A. Data Collection

The recordings used in this study were obtained from 19 patients recruited from a specialized cough clinic. The causes of cough in these patients were: cough variant asthma $(n = 5)$, eosinophilic bronchitis $(n = 3)$, gastro-oesophageal reflux $(n = 3)$, idiopathic $(n = 3)$, postviral $(n = 2)$, bronchiectasis $(n = 1)$, chronic bronchitis $(n = 1)$, and chronic obstructive pulmonary disease $(n = 1)$.

The recordings were all started in the morning and lasted for an average of 6 h, during which period the subjects were encouraged to perform their usual daily routines.

The recording system consists of a portable digital audio recorder (ARCHOS Jukebox Recorder 20, Archos (UK) Limited, Andover, U.K.) and a miniature condenser microphone (Sennheiser MKE 2–5, Sennheiser electronic GmbH & Co. KG, Wedemark, Germany) with a flat frequency response between 20 and 20 kHz. The microphone is attached to the subject's chest and is powered by a battery pack that is carried, together with the recorder, on a shoulder-bag.

The audio is recorded at a sampling frequency of 16 kHz and stored in MPEG audio layer-3 (MP3) format [9]. This compressed audio format was used because it enables a more efficient storage of data and a faster upload from the recording device to the personal computer for analysis. We compared signals obtained from voluntary cough sounds, recorded simultaneously to a digital audio tape recorder, a portable digital recorder using an uncompressed format (WAV) and the MP3 recorder and obtained average normalized mean square errors lower than 2% at a sampling frequency of 16 kHz. Fig. 3 shows an example of a voluntary cough sound recorded using the three recording systems.

TABLE I
RECOGNITION RESULTS FOR EACH TEST RECORDING

Recording number	Number of cough events	Cough events per hour	Detected cough events (%)	Number of FAs per hour
1	597	83	56	15
2	132	24	58	8
3	63	10	94	17
4	466	73	52	10
5	34	7	50	7
6	93	15	84	3
7	204	44	99	31
8	193	52	76	24
9	373	60	71	2
Average	239	41	71	13
St. Dev.	195	28	18	10

The recordings were uploaded to a personal computer, converted to WAV format and divided into 10-s segments, to facilitate the analysis. The audio signals were high-pass filtered using a second-order digital Butterworth filter with cutoff frequency at 100 Hz. The resulting audio files were then listened to and analyzed by visual inspection and each sound identified as a cough was individually labeled, by marking its starting and end points. These labels are used both for training and for testing the algorithm.

The training data consists of 821 min and includes 2473 cough signals. All of the segments from the first 10 recordings that contained cough sounds were selected, plus some randomly selected segments from these recordings that contain background sound only. The remaining nine recordings were used as test data. The average number of cough events in the test recordings was 239 (range 34–597 events), which corresponds to an average of 41 (7–83) cough events/h (Table I).

The HTK [7] toolkit was used for training and recognition and also for the feature extraction step. Matlab (The MathWorks, Inc., Natick, MA) was used to segment and filter the uncompressed audio files and to run the HTK scripts.

B. Feature Extraction

The first stage in the recognition algorithm is to convert the audio data into a parametric representation used to describe each frame of data. The most important types of parametric representation used in speech recognition are filter-bank outputs, linear predictive coding (LPC) coefficients and Mel frequency cepstral coefficients (MFCC) [6].

The MFCC parameterization describes the properties of a frame of audio data in the cepstal domain. The complex cepstrum is defined as the Fourier transform of the logarithm of the signal spectrum and the cepstral coefficients $c(n)$ for a signal with power spectrum $S(w)$, are given by the Fourier series coefficients of the logarithm of $S(w)$ [6]

$$\log\left(S(w)\right) = \sum_{k=-\infty}^{\infty} c(n) \cdot \exp(-jnw). \tag{1}$$

The mel frequency scale is a variant of the critical band scale, which is based on perceptual studies and intends to select frequency bands with equal contribution to speech articulation. MFCCs can be calculated from the output of a bank of triangular shaped bandpass filters, distributed along a mel scaled frequency band of interest. The filter bandwidth and spacing are constant for frequencies below 1000 Hz and exponential for frequencies above 1000 Hz [6].

If S_k are the filter power outputs of a K channel mel frequency filter bank, then the MFCCs can be calculated as [6], [7]

$$c(n) = \sum_{k=1}^{K} \log(S_k) \cdot \cos\left(\frac{n\pi}{K}(k-0.5)\right) \quad n = 1, 2, \ldots, N \tag{2}$$

where N is the number of cepstral coefficients to calculate. We used this parameter type because it provided good discrimination results for cough sounds.

A total of 13 MFCCs were calculated from the outputs of a 16-channel filter-bank, including the zeroeth-order cepstral coefficient, which gives a measure of signal energy in the frame [7]. The first and second-order derivatives of these coefficients were also calculated, producing a total of 39 features for each time frame.

Cepstral coefficients present a wide range of variances, with higher order coefficients having much smaller values than low-order ones. To overcome this, cepstral liftering is usually applied to rescale the coefficients, according to the following formula [7]:

$$c'(n) = \left(1 + \frac{L}{2}\sin\left(\frac{n\pi}{L}\right)\right) \cdot c(n). \tag{3}$$

We used cepstral liftering, with $L = 22$, and cepstral mean normalization, which removes the mean of the cepstral coefficients, was also applied, to account for the different recording conditions encountered and to normalize the frame energy values within a 10-s segment. Although the absolute energy information is lost during this procedure, this produces better generalization and allows detection of quieter cough sounds.

The frame rate was 16 ms and a 32-ms Hamming window was used, giving a total of 624 frames for each 10-s segment of the recordings.

C. Hidden Markov Models

HMMs are a statistical method that can be used to characterize the spectral properties of a time-varying pattern. The HMM approach allows the characterization of speech signals (or other temporal signals) as a parametric random process and provides a precise manner to estimate the parameters of that process [6].

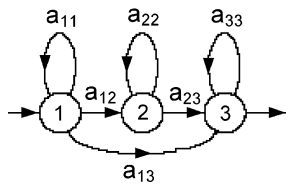

Fig. 4. HMM structure (left-to-right).

A Markov model is a finite state machine that changes from state i to state j at every time instant t depending on a transition probability a_{ij}, as shown on Fig. 4. Each time a state j is reached, a signal vector o_t is output from the model, depending on the probability density $b_j(o_t)$ for that state [6].

An HMM is characterized by the following parameters [6], [7]: N is the number of states in the model; $A = \{a_{ij}\}$ is the state-transition probability distribution; $B = \{b_j(k)\}$ is the observation symbol probability density function; $\pi = \{\pi_i\}$ is the initial state distribution.

The probability density function for continuous output symbols is usually modeled by a finite mixture of the form [6]

$$b_j(\mathbf{o}) = \sum_{k=1}^{M} c_{jk} \cdot \Psi(\mathbf{o}, \boldsymbol{\mu}_{jk}, \mathbf{U}_{jk}) \quad j = 1, 2, \ldots N \tag{4}$$

where $\boldsymbol{o}$ is the observation vector, c_{jk} is the k^{th} mixture coefficient for state j and Ψ is the distribution function for the k^{th} mixture component in state j. Ψ is usually assumed to be Gaussian, with mean vector $\boldsymbol{\mu}_{jk}$ and covariance matrix $\mathbf{U}_{jk}$.

Given a sufficient number of examples of a specific signal, the parameters of a HMM can be efficiently estimated so that it models the characteristics of the signal [6], [7]. Once the model parameters are estimated, the recognition process evaluates, for a given observation sequence, the likelihood of that observation sequence being produced by the model. If different models are trained, then it is possible to decide which model is more likely to have produced that given output.

D. Event Spotting Using HMMs

We trained three different models to represent the cough signals and 128 "filler" models. The "cough" models have a left-to-right structure, with 10, 15, and 20 states, respectively, and with valid transitions to the same or the next state only. The "filler" models also have a left-to-right structure, with three states, and an additional valid transition from the first to the third state, as shown in Fig. 4. Each state's observation symbol probability density function is modeled by a mixture of 12 Gaussian functions for the "cough" models and three Gaussian functions for the "filler" models.

The three "cough" models were firstly initialized and trained using the "cough" labeled portions of the training data. These training "cough" events were then assigned to the model with the highest likelihood and each model was retrained using the patterns assigned to it. This procedure was repeated four times and was stopped when the clusters converged, i.e., the training patterns did not change from one model to another.

The number of Gaussian functions for each state of the "cough" models was gradually increased from 1 to 12. The "cough" patterns were redistributed between models and the models retrained after each Gaussian was added.

"Filler" models were created iteratively: a first model was created and its state's mean and variance vectors were set to the global mean and variance of the training data. Two new "filler" models were then created from this initial model by, respectively, adding and subtracting a small value (set at 0.01) to the elements of each state's mean vector. The two new models were then used to recognize the training data, thus creating a segmentation of the data, and this segmentation result was used to retrain the models. This procedure was repeated until the required number of "filler" models was obtained.

The next step was to train the "cough" and "filler" models simultaneously, by performing three iterations of embedded training, as described in [7]. After this, the number of Gaussian functions in the "filler" models' states was gradually increased to three Gaussians per state, again followed by three repetitions of embedded training, at each stage. The number of iterations for embedded training and the number of Gaussian functions in the models were selected empirically, by testing the performance on a validation set.

The recognition process works by finding the sequence of models that fits an unknown input frame sequence with the highest probability. For each individual test recording, the 10-s segments are sequentially presented to the recognizer and analyzed individually. For each test segment, the recognizer finds the path through the states of "cough" and "filler" models that produces the highest probability for that sequence of frames. This probability is calculated by summing the probabilities of each transition in the path and the probabilities of each model's state generating the corresponding observation feature vector. The best path is found by a token passing algorithm, as described in [7].

This recognition process was executed at nine times the real-time of the recordings, using a personal computer with an Intel Pentium 4 1.50-GHz processor and 768-MB of RAM.

The recognition result for each test segment is a sequence of "filler" and (possibly) "cough" models and their time localization within that segment. To evaluate the results, each occurrence of a "cough" model in the recognition output is compared with the manually created labels. If the middle point of a manually labeled cough signal occurs within the start and end times of the "cough" model in the recognizer output, then that detected event is identified as a correct detection (hit); otherwise it is identified as an incorrect detection (FA). The recognizer performance is then evaluated in terms of the percentage of correct detections (hits) and the number of FAs produced per hour.

III. Results

Table I shows the results obtained when running this recognition process on the test recordings. The average detection result is 71% at a FA rate of 13 events/h, when no energy threshold is used for the recognition.

FAs are obtained when different sounds are detected as cough sounds by the algorithm. The main source of FAs on the test recordings were short segments of speech, which produced an

TABLE II
RECOGNITION RESULTS FOR EVENTS ABOVE 90% ENERGY LEVEL

Recording number	Number of cough events	Detected cough events (%)	Number of FAs per hour
1	287	77%	10
2	89	64%	4
3	60	95%	13
4	407	58%	8
5	34	50%	4
6	87	90%	2
7	196	99%	24
8	134	90%	16
9	353	73%	1
Average	183	77	9
St. Dev.	136	17	8

TABLE III
RECOGNITION RESULTS FOR EVENTS ABOVE 95% ENERGY LEVEL

Recording number	Number of cough events	Detected cough events (%)	Number of FAs per hour
1	169	80%	5
2	66	77%	4
3	48	96%	11
4	329	67%	6
5	32	53%	4
6	81	94%	2
7	192	99%	22
8	120	90%	13
9	301	78%	1
Average	149	82	7
St. Dev.	108	15	7

average (standard deviation) of 4 (6) events/h. Throat clearing sounds, impulsive noises and cough sounds from other persons were the other main sources of FAs.

The algorithm's performance was also tested at two different energy levels, by taking into account only those events with root mean square (RMS) energy above a relative energy threshold. The energy thresholds used were calculated for each individual recording as the 90% (CDF90) and 95% (CDF95) points of that recording's energy cumulative density function (CDF).

Table II shows the number of cough events above the CDF90 energy threshold for each individual recording, together with the recognition results. An average of 84% of the labeled events on the test recordings are above the CDF90 energy level and 77% of these events are correctly identified by the algorithm, at a FA rate of nine events/h.

The recognition results for events above the CDF95 energy level are shown in Table III. An average of 72% of the cough events are above this energy level and the algorithm is able to correctly identify 82% of these events, with a FA rate of seven events/h.

IV. DISCUSSION

These results show that we are able to detect a high percentage of cough events in a completely automated manner. The algorithm's performance is influenced by the energy level of the cough signals, with low energy signals producing a lower detection rate. When considering events above an energy threshold calculated for each recording the percentage of correctly identified events increased, with lower FA rates.

Previous studies on long-time monitoring of cough have relied on trained operators to analyze the recordings in order to count the existing cough events [3]–[5]. In [4], the audio data is divided into 1-s buffers and only those segments containing signal with energy above a certain threshold are saved. These segments of data are then replayed and the signal waveform displayed to allow identification of cough sounds by a trained observer.

Our system is based on statistical models of the time-varying characteristics of cough audio signals to detect the occurrence of cough sounds in continuous recordings. The models used are able to represent cough sounds with different characteristics, but the algorithm's sensitivity could be improved if more data were available for training the models. It would also be useful to separate the cough sounds into groups with similar characteristics and train a separate model for each group.

The number of FAs returned by the automatic detection algorithm prevents the direct use of the result without further manual analysis. Some of the FA events are caused by low energy signals, and we are improving the energy threshold calculation to vary dynamically within each recording, to reject segments with low energy. We are also implementing a second recognition stage to the algorithm to allow identification and rejection of sounds like speech and throat clearing.

At this stage, the automatic algorithm needs to be followed by a manual analysis stage in which a trained observer can listen to the detected sounds and eliminate the incorrectly identified ones. The signals returned by the algorithm are isolated sounds that are correctly segmented, allowing this analysis stage to be performed in a fast and easy manner.

V. CONCLUSION

We have evaluated an innovative way to automatically detect cough sounds from ambulatory recordings, which can be used to calculate cough frequency and aid in the assessment of patients with chronic cough and other conditions. Currently, the algorithm can be used to extract candidate events from long recordings, for further manual analysis by a trained observer. The algorithm's output makes this analysis faster and easier for the operator. Further work is under way to reduce the number of false-alarms returned by the algorithm and eliminate the necessity of a manual analysis stage.

The models used for representing cough sounds could be improved by using more training data and by creating models for groups of similar cough sounds. The results could also be improved by using a postprocessing stage for the algorithm, to reject some of the false-alarms obtained.

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