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Towards a quantitative description of asthmatic cough sounds

C.W. Thorpe, L.J. Toop, K.P. Dawson*

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ABSTRACT: This study describes a method of quantitatively characterizing cough sounds using digital signal processing techniques. Differences between asthmatic and non-asthmatic cough sounds are presented.

Coughs from 12 asthmatic and 5 non-asthmatic subjects were analysed. Cough sounds and flows were digitized, at a sampling rate of 5 kHz, before and after a free-running exercise test. Individual coughs were divided into two or three phases, corresponding to the initial glottal opening burst, the quieter middle phase, and (sometimes) the final closing burst. Standard signal processing techniques were then invoked to characterize the spectral and temporal shapes of the first two phases.

Factor analysis indicated that the spectral shapes of the two phases are independent, with each being largely described by the degree of "peakedness" in the spectrum, and by the balance of energy between low and high frequencies. Both the duration of the initial burst and zero-crossing rates of the cough waveform (which indicates the "spectral balance") during each of the first two phases were smaller for asthmatic than for non-asthmatic coughs. Fewer asthmatic coughs contained a final burst. Discriminant analysis between the two groups gave classification error rates of 20–30%. The peak flow recorded during the cough was significantly smaller for asthmatics, and correlated very well with the peak flow recorded during forced expiration.

Thus, significant differences exist between asthmatic and non-asthmatic cough sounds. An effective representation of the temporal structure of the cough sound is required to successfully characterize the cough.

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Cough is an important symptom in many respiratory diseases [1]. Also, cough is sometimes the only presenting symptom of asthma [2]. The ability to describe and characterize the cough sound in asthma and other respiratory diseases should therefore be diagnostically useful [3]. In order to fully utilize the diagnostic information carried by cough sounds, it is first necessary to develop methods of quantifying their characteristics. In this paper we discuss the approach that we have taken to characterize patterns in the cough sounds of children with and without asthma, before and after exercise.

KORPAS *et al.* [4] and SALAT *et al.* [5] characterized coughs by their "tussiphonogram", which is the cumulative integral over time of the cough sound intensity. They found that the overall cough intensity is significantly less during asthma. However, they report no significant correlation between the sound characteristics and the results of spirometric assessment of airway function [4].

DEBRECZENI and co-workers [6, 7] computed average spectra of cough sounds from patients with various respiratory diseases. They then determined the frequency bands over which the sound energy differed significantly between each pair of diseases. In contrast, PIIRILA and SOVIJARVI [8] computed average spectra from which they extracted the peak and highest frequency components. They also computed spectrograms (time *versus* frequency graphs) of the sounds, from which they determined the duration of the cough sound and any wheezing components. In their results, asthmatic coughs were characterized as being relatively long, or having a prolonged wheezing sound, and with a low upper frequency limit to their average spectrum.

In a preliminary study of cough sounds from children with and without asthma [9], we computed spectrograms which suggested that exercise produced changes in the cough sounds of asthmatic but not of normal children. However, no quantitative measurements of these changes were made.

Methods

Subjects

Twenty four children with clinical asthma drawn from a paediatric out-patient clinic were studied. All required the use of prophylactic asthma treatment.

Eight children with neither personal nor familial histories of asthma were used as controls.

All drugs were withheld for at least 12 h before the cough sounds were collected. Six children with active upper respiratory tract infections were excluded from the study. Pre-exercise spirometry was performed and checked with predicted values (based on standard height tables). Four children were excluded because their peak expiratory flow rate (PEFR) at rest was <75% of expected, while two children with clinical asthma were excluded because the maximum drop in their PEFR after exercise was <15%. A further three children were excluded because their cough sounds did not contain a middle phase, as required by our analysis methodology. Table 1 summarizes the characteristics of the remaining 12 asthmatic and 5 non-asthmatic subjects whose coughs were employed in the statistical analyses presented here.

Table 1. – Details of subjects employed in the study

	Asthma	Control
Subjects n	12	5
Age yrs	9	10
	(6–14)	(8–11)
Height cm	134	142
	(121–166)	(133–155)
Sex M/F	10/2	2/3
Pre-ex PEFR % pred	95	105
	(80–138)	(85–112)
Max post-ex PEFR drop %	42	10
	(17–75)	(6–12)

Data for age, height and PEFR are given as mean and range in parenthesis. PEFR: peak expiratory flow rate; ex: exercise.

Data collection

Subjects coughed through a custom-built pneumotachograph to record the airflow during the cough [10]. A microphone (Beyer Dynamic MCE 6) was attached to the exhaust end of the flow meter. The sound signal was low-pass filtered at 2.5 kHz and sampled at a rate of 5 kHz by a 12 bit A/D converter (Analog Devices RTI-815). The flow signal was simultaneously sampled at 500 Hz. The signals were stored on an IBM PC-AT compatible microcomputer for analysis [10].

Children were instructed to make a single voluntary cough. However, a few subjects made multiple coughs. Only the first cough of such series was analysed. Voluntary cough sounds were collected before and after a standard six minute free running exercise test [11]. Baseline spirometric data and a pre-exercise voluntary cough were collected, then further coughs and PEFR values were obtained at 2, 4, 6, 8, 10 and 15 min post-exercise, a total of seven coughs per subject. Three asthmatic and two non-asthmatic post-exercise coughs (from different subjects) were excluded because of faulty recordings, so that a total of 114 coughs was analysed. The number of coughs actually employed in each analysis is specified in the results.

Signal processing

Cough phases. Each cough sound was divided into two or three phases as indicated in figure 1 [4, 12].

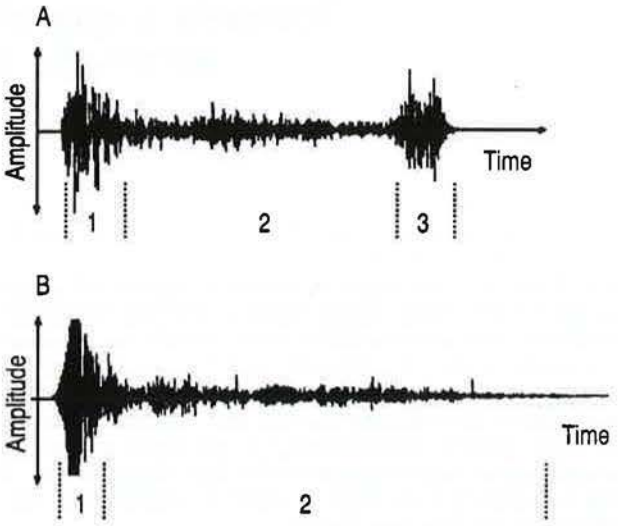

Fig. 1. – Examples of typical cough sounds, showing the division into two or three "phases". The numbers between the dashed lines indicate the phases, thus: 1=initial burst; 2=middle phase; and 3=final burst. (A) a cough which exhibits all three phases. (B) a cough with no final burst.

The phases are termed the "initial burst", which consists of an explosive burst of sound energy and corresponds to the glottal opening transient; the "middle phase", which is generally quieter and corresponds to an interval of steady-state flow with the glottis wide open; and the "final burst", which is produced as the airflow is arrested by the closing of the glottis. The final burst is only present in some coughs. These three phases correspond to the "first cough sound", "noisy interval", and "second cough sounds" of KORPAS *et al.* [4].

In order to identify the cough phases, we developed a semi-automatic segmentation procedure. An initial segmentation was performed automatically, based on the amplitude of the sound envelope (which was computed as the root mean square value of 10 ms segments spaced every 5 ms throughout the sound record). The positions of the phases were then interactively examined and adjusted according to the aural impression of the cough sound. The following rules define how the phases were identified. Note that the particular threshold values invoked in the procedure are somewhat arbitrary, but were chosen so that the procedure identified phase transitions that were subjectively similar to those described by KELEMEN *et al.* [12]. We do not claim that this is the only method of subdividing cough sounds:

1. The start of the initial burst is positioned at the instant when the envelope of the sound first exceeds 1/20th of its peak value.
2. The start of the middle phase is positioned immediately after the sound envelope has dropped by >75%

of its peak value. In coughs where this point is not clear because of the high intensity of the middle phase sound, the trial middle phase segment is replayed and the start point interactively adjusted until no "initial burst" can be heard.

3. The end of the cough is automatically located at the instant where the sound envelope falls below 1.75 times the amplitude of the background noise. The background noise level is determined by averaging the values of the sound envelope within the cough record that are less than twice the amplitude of the smallest non-zero value.

4. The final burst is deemed to be present if either the peak amplitude of the sound envelope in the second half of the cough is greater than 3 times the minimum amplitude of the sound envelope in the interval before the peak, or if the cough finishes with a "voiced" burst (which may be of low intensity). The start of the final burst is positioned interactively by adjusting the trial position and listening to the middle phase sound until the final burst cannot be perceived.

Spectral analysis. Spectrographic analysis was performed on the sound signal by Fourier transforming [13] 256 sample (51 ms) long segments of sound, with the start of adjacent segments being separated by 50 samples (10 ms). A Hamming window [13] was applied to each segment before the fast Fourier transform was computed.

From each phase of a cough, an average spectrum was computed by summing individual spectral lines. Because the flow meter and mouthpiece modifies the character of the recorded sound, their estimated acoustic response was deconvolved from the average spectrum by Wiener filtering [13] before the features were extracted [14].

Feature extraction. Normalizing the average power spectrum to have unit energy allows it to be treated as a probability density function. We computed the mean frequency (MF), the standard deviation (STDF), the skewness (SKF), and the kurtosis (KTF) of the distribution of energy within the spectrum. We also computed the logarithm of the total power in the average spectrum (TOTEN) and the proportion of power within the frequency bands 0–500 Hz, 500–1,000 Hz, 1–1.5 kHz, and 1.5–2.5 kHz (SUB1–SUB4, respectively). Finally, the shape of the average spectrum was also characterized by calculating the first four cepstral coefficients (C1–C4). Cepstral coefficients are the Fourier coefficients of the log power spectrum [13].

Several variables were also estimated from the time domain waveform of each phase. These were the duration (DURAT), the ratio of the maximum to minimum log root mean square (RMS) amplitude within the phase (MTOM), and the average zero-crossing rate (ZCR).

The cough flow was characterized by the peak (PKFLOW) and average (AVFLOW) flow rates in each phase.

The variables are identified in the remainder of this paper by the mnemonics defined above, together with a suffix indicating which phase it is associated with. Thus, ZCR-I refers to the zero-crossing rate of the initial burst, whilst ZCR-M refers to that of the middle phase.

Statistical analysis. Principal component analysis (PCA) was performed on the feature variables obtained from all the coughs in order to identify any common variables. The results of the PCA were interpreted qualitatively, with the magnitudes of the factor loadings being used as a guide to which feature variables were characterizing similar aspects of the cough sound. The varimax rotation was applied to the factors in order to simplify the interpretations.

Student's t-tests were employed to determine which feature variables differed significantly between the asthmatic and non-asthmatic groups. The results were interpreted in an indicative sense, with the relative sizes of the significance levels implying an ordering of the variables in terms of their discrimination performance.

Multivariate discriminant analysis was performed to identify groups of variables that jointly distinguished asthmatic from non-asthmatic coughs. Subsets of variables were selected by means of the stepwise discriminant approach [15]. A maximum of five variables was employed in each analysis. In order to test the effectiveness of the discriminant analyses, classification error rates were estimated for each model, by means of the cross-substitution "jack-knife" approach [16].

The t-tests and discriminant analyses were both performed on the feature variables extracted from the ensemble of coughs obtained both before and after exercise, and also on the pre-exercise to post-exercise change in the feature variables. In order to increase the number of coughs in each post-exercise time, the pre-exercise to post-exercise differences were assembled into three groups, with coughs at 2 and 4 min, 6 and 8 min, and 10 and 15 min, respectively, bracketed together.

Results

Phases

Of the 33 non-asthmatic coughs, 21 had a final burst, compared with only 22 of the 81 asthmatic coughs ($Chi^2=13$, $p<0.0001$). Because so many of the coughs have no final burst, it is useful to examine the dependence of the phase 1 and 2 feature parameters on the presence or absence of the final phase. A two-way analysis of variance (ANOVA) was constructed with the presence of asthma and the presence of a final burst as main effects. The only variables to differ significantly with the presence or absence of the final burst were DURAT-M ($F=30$, $df=1$, $p<0.0001$) and MTOM-M ($F=140$, $df=1$, $p<0.0001$). Neither variable, however, differed with the presence or absence of asthma. Only the phase 1 and phase 2 feature variables are employed in the analyses presented here.

Principal component analysis

PCA of variables from phases 1 and 2 of the cough was performed. Cattel's scree test [17] identified five significant factors, accounting for 62% of the variance in the data set. The factor loadings are itemized in table 2. The first two factors group together those variables that characterize the overall spectral "balance" of the middle and initial phases, respectively. Factor 3 groups together the middle phase variables KTF-M, STDF-M, SUB2-M, and C3-M, whilst Factor 4 comprises the initial burst variables KTF-I, SKF-I, C2-I, together with DURAT-M. Factor 5 reflects further aspects of the initial burst, SUB1-I, SUB2-I and C4-I.

Table 2. – Rotated factor scores for the PCA conducted on all the cough variables

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
MF-M	0.9	0.3	0.1	0.1	0
SUB4-M	0.7	0.2	0.4	0.4	-0.2
ZCR-M	0.7	0.1	0.5	-0.1	-0.1
SUB1-M	-0.7	-0.4	0.4	0.1	0
SKF-M	-0.8	0.1	-0.1	0.2	-0.2
C1-M	-0.8	-0.2	-0.5	-0.3	0.2
MF-I	0.2	0.8	-0.3	-0.2	-0.2
SUB4-I	0.1	0.8	0.1	0.2	0.1
ZCR-I	0.1	0.8	0.1	-0.3	0.2
STDF-I	0.1	0.7	0.2	0.1	0.6
C1-I	-0.3	-0.8	0.3	-0.2	-0.1
C3-M	0.1	-0.2	0.7	-0.1	0
STDF-M	0.2	0.1	0.7	0.4	-0.2
KTF-M	-0.3	-0.1	0.6	0.5	-0.3
SUB2-M	-0.2	0.2	-0.7	0	-0.3
DURAT-M	0.1	0	-0.2	0.7	-0.2
SKF-I	0	0	0.1	0.7	0.4
C2-I	0	-0.5	0	0.7	-0.1
KTF-I	0.1	0.4	0.1	0.6	0.5
SUB1-I	-0.2	-0.5	0.5	0.2	0.6
C4-I	0	0.2	-0.1	-0.2	0.6
SUB2-I	0.1	-0.1	-0.4	0	-0.8
TOTEN-I	0.4	0	-0.1	0	0.1
TOTEN-M	0.4	0.1	-0.3	-0.1	0.3
DURAT-I	-0.2	0.1	0.4	-0.1	0
TOTDURAT	0	0.1	0.1	0.5	-0.1
MTOM-I	-0.1	0	0.1	0	-0.4
MTOM-M	0	-0.1	-0.4	0.5	0.1
C3-I	0.1	-0.1	0.5	0	0.4
C2-M	-0.5	-0.3	0.1	0.5	-0.3
C4-M	0	-0.3	0	-0.3	0.4
Variance explained %	14	14	12	12	10

Factor scores >0.5 are underscored. Variables are ordered according to the factor to which they have the highest correlation. PCA: principal component analysis; MF: mean frequency; SUB4: frequency band 1.5–2.5 kHz; ZCR: zero crossing rate; SUB1: frequency band 0–500 kHz; SKF: skewness; C: cepstral coefficient; STDF: standard deviation; KTF: kurtosis; SUB2: frequency band 500–1,000 kHz; DURAT: duration; TOTEN: total power in the average spectrum; TOTDURAT: total duration; MTOM: maximum to minimum log RMS amplitude within the phase; M: middle phase; I: initial burst; RMS: root mean square.

Several of the variables are not well represented by the five factors, as evidenced by their small factor loadings. Notably, the variables DURAT-I, TOTDURAT, MTOM-I, MTOM-M, TOTEN-I, TOTEN-M, C3-I, C4-I and C4-M have maximum factor loadings and communalities that are both ≤0.5.

Table 3. – Significant differences between means of feature variables for asthmatic and non-asthmatic groups

A

Variable	Mean Asthma	Mean Control	SD	p
	(n=81)	(n=33)		
ZCR-M Hz	1000	1130	170	0.0001
ZCR-I Hz	680	780	120	0.0002
DURAT-I ms	54	70	24	0.002
MTOM-M	2.8	2.1	1.1	0.002
STDF-I Hz	380	430	80	0.007
STDF-M Hz	520	570	90	0.02
C1-I	15	12	4.2	0.02
C1-M	7.0	5.0	4.1	0.02
C2-I	-3.3	-4.6	3.5	0.03
C2-M	-4.9	-6.6	4.1	0.05
C4-I	-2.7	-1.1	3.5	0.03
MF-M Hz	860	960	230	0.03
SUB3-I	0.15	0.21	0.13	0.03
SUB4-M	0.16	0.22	0.11	0.03

B

Variable	Mean Asthma	Mean Control	SD	p
1	(n=23)	(n=9)		
ZCR-M Hz	80	-90	200	0.05
2	(n=22)	(n=9)		
C4-I	3.0	-1.5	4.4	0.02
DURAT-I ms	-13	12	22	0.02
SUB3-I	0.08	-0.06	0.15	0.03
SKF-M	-17	290	340	0.03
3	(n=24)	(n=10)		
ZCR-M Hz	40	-180	150	0.001
SKF-M Hz	-30	370	420	0.02
SUB2-M	0.02	0.15	0.15	0.04
C2-M	0.3	-2.5	3.5	0.05
4	(n=69)	(n=28)		
ZCR-M Hz	60	-120	180	0.0001
SKF-M Hz	-25	310	410	0.0005
C2-M	0.67	-2.1	4.0	0.004
SUB2-M	-0.002	0.09	0.15	0.02
C4-I	1.7	-0.4	4.0	0.02
KTF-M Hz	-13	50	80	0.04
MTOM-I	0.08	-0.5	1.0	0.04
SUB4-M	-0.02	-0.08	0.12	0.05

A total of 32 variables were tested, but only those that are individually significant at the 0.05 level are included here. Note that the Bonferroni criterion implies that only the variables with $p<0.002$ are significantly different at an experiment-wide significance level of $p=0.05$. A) Variables from all coughs grouped together. B) Pre-exercise to post-exercise differences, with groups of coughs from: 1) 4 min; 2) 8 min; 3) 12 min; and 4) all post-exercise times. For abbreviations see legend to table 2.

Asthmatic/non-asthmatic differences

The differences between the asthmatic and non-asthmatic groups of coughs for each of the features were evaluated by means of Student's t-test. Table 3A lists those feature variables that differ significantly between the two groups of coughs. Note that only the variables DURAT-I and ZCR-I from the initial burst, and MTOM-M and ZCR-M from the middle phase, exhibit a difference between the two groups at the experiment-wide $p<0.05$ level (the Bonferroni criterion implies that only the variables with $p<0.002$ are significantly different at an experiment-wide significance level of $p=0.05$). Figure 2 shows a scatter plot of DURAT-I *versus* the normalized PEFR values. The Pearson correlation coefficient between these two variables is 0.38.

Table 3B lists the variables with significantly different pre-exercise to post-exercise changes between the two groups. Results are shown, firstly for the coughs grouped according to their time of occurrence after exercise, and secondly for a grouping of all the pre-exercise to post-exercise differences.

Multivariate discriminant analysis

Table 4 shows the variables that are selected, together with the resulting significance levels, when features are selected using: A) the ensemble of all coughs; and B) the pre-exercise to post-exercise changes in the coughs.

The F statistics in the first and second columns of the table are the partial statistics of adding in the new variable to the variables already in the model. The fourth column contains Wilks' Lambda statistic, which is the ratio of within group to total group scatter. Estimated error rates are shown in the fifth column.

Table 4. – Results of the stepwise discriminant analysis conducted in order to determine subsets of variables that jointly distinguish asthmatic and non-asthmatic coughs

Variable	Statistics of new variable F	p	Multivariate statistics Lambda	Estimated error rate %
A				
ZCR-M	15	0.0001	0.88	30
+DURAT-I	13	0.0005	0.79	25
+ZCR-I	8	0.006	0.74	24
+C3-I	4	0.05	0.71	20
+SUB1-I	3	0.09	0.69	24
B				
ZCR-M	17	0.0001	0.85	27
+C4-I	12	0.0008	0.75	29
+C2-M	14	0.0003	0.65	24
+TOTEN-M	8.5	0.004	0.59	21
+SKF-M	10	0.002	0.54	18

Each line of the table indicates an additional variable that is added to the model. The F statistics in columns 2 and 3 are computed from an analysis of covariance of the new variable against the variables already in the model. The 4th column contains Wilks' Lambda, computed from the multivariate distribution, while the final column has an estimated classification error rate, obtained *via* the cross-validation "jack-knife" approach. A) Analysis of the actual feature values of all coughs. B) Analysis of the pre-exercise to post-exercise changes in the feature values (all coughs). For abbreviations see legend to table 2.

Cough flow

The four flow variables are all highly correlated, with Pearson correlation coefficients ranging from 0.78 (AVFLOW-I and AVFLOW-M) to 0.92 (AVFLOW-M and PKFLOW-M). They also correlate well with the

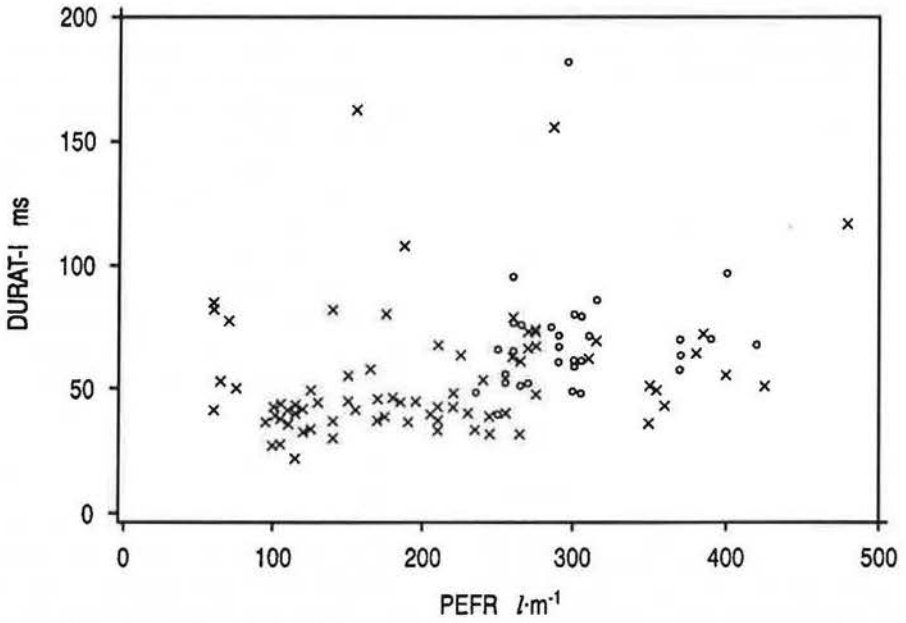

Fig. 2. – Scatter plot showing the duration of the initial burst (DURAT-I) of each cough sound plotted against the peak flow recorded during a forced expiration (PEFR) at the time of each cough. X: asthmatic; O: control.

spirometric PEFR values (r=0.85 between PEFR and both PKFLOW-M and AVFLOW-M). Figure 3 shows a scatter graph between PKFLOW-I and corresponding PEFR values (r=0.79).

As implied by the high correlation to spirometric results, the cough flow variables discriminate well between asthmatics and normals. Table 5 shows the results of t-tests on both the raw flow values and on the pre-exercise to post-exercise changes.

The flow variables are correlated with only a few of the sound variables. The largest correlations are between TOTEN-I and PKFLOW-I (r=0.42), STDF-M and PKFLOW-M (r=0.46), DURAT-I and AVFLOW-I (r=0.38), SUB1-I and AVFLOW-I (r=0.38), SUB4-M and AVFLOW-M (r=0.38), and C3-M and PKFLOW-I (r=0.37).

Discussion

One of the difficulties of classifying cough sounds into different "types" corresponding to different diseases is that the sounds vary in many different ways, not all of which are relevant to changes induced by the disease. The results presented here indicate that a multivariate discrimination approach is necessary in order to incorporate the information contained in the several significant but uncorrelated variables. Multivariate analysis is necessary to adequately describe changes in the spectral shape, since spectral shape cannot usually be adequately characterized with a single variable.

Note that all the analyses were performed with at least some repeated coughs from each subject.

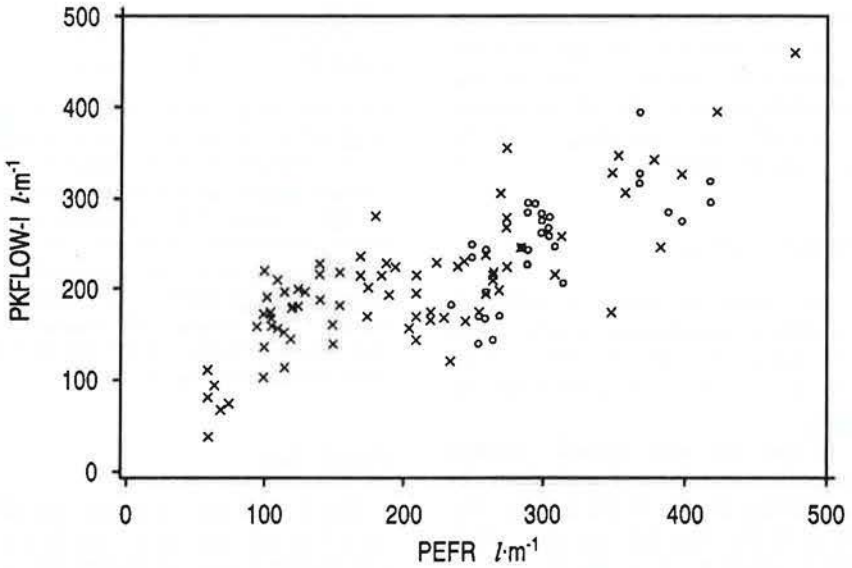

Fig. 3. – Scatter plot between the peak air flow recorded during the initial burst of a cough (PKFLOW-I) and that obtained from a forced expiration (PEFR). X: asthmatic; O: control.

Table 5. – Significance levels of the cough flow variables as asthma/non-asthma discriminators

Variable	Means		SD	p
	Asthma	Control		
A	(n=79)	(n=33)		
PKFLOW-I	200	246	70	0.0009
PKFLOW-M	120	180	50	0.0001
AVFLOW-I	100	127	45	0.007
AVFLOW-M	83	135	40	0.0001
B	(n=63)	(n=28)		
PKFLOW-I	-54	4	60	0.0001
PKFLOW-M	-68	0	50	0.0001
AVFLOW-I	-40	1	42	0.0001
AVFLOW-M	-46	-9	25/43	0.0002*
PEFR	-107	-21	60/13	0.0001*

All values are in $l \cdot s^{-1}$. Note that two coughs were excluded because of gross errors in the flow measurement. A) All coughs, raw data values. B) Pre-exercise to post-exercise changes. *: unequal standard deviations. PKFLOW: peak flow; AVFLOW: average flow; PEFR: peak expiratory flow rate.

This means that the assumption that each observation is independent is not strictly met. However, because we only interpret the results in an indicative sense, such dependencies do not invalidate our results.

The factor analysis performed on all the feature variables revealed several factors which appear to correspond to physical characteristics of the cough sound. Two of the factors can be thought of as corresponding to the spectral balance of each of the first two phases of the cough sound (Factors 1 and 2). Factors 3 and 4, meanwhile, indicate the spectral flatness of each phase, with variables such as STDF and KTF that represent the spectral "peakedness". Factor 5 represents the distribution of initial burst energy between the low frequency sub-bands SUB1-I and SUB2-I.

Apart from DURAT-M in Factor 4 and some correlation between the initial and middle phase cepstral coefficients C2, C3 and C4, none of the factors contain mixtures of variables from the two phases. This implies that the separation into phases usefully reflects the actual structure of the cough sound. It would

appear that the sound structure of the first two phases is not highly correlated, which suggests that the two sounds have distinct origins. This accords with previous work on the sources of the cough sounds [4].

Several of the variables, notably the time-domain variables (apart from DURAT-M) and some of the cepstral coefficients, are largely uncorrelated with any of the other variables. This is partly a result of an over-abundance of spectral shape variables, some of which are obviously superfluous. It also implies that the temporal structure of the cough is largely uncorrelated to the spectral characteristics of each phase. In addition, the temporal shape variables chosen by us are also uncorrelated with each other, with only DURAT-I and MTOM-M significantly discriminating asthmatics. We think that it would be useful to devise new variables that better represent the temporal structure of the cough sound. Similarly, the cepstral coefficients are a more orthogonal representation of the spectral shape than the central moments or sub-band variables.

Several of the variables exhibit significant differences between the asthmatic and non-asthmatic groups when tested on their own. Notably, ZCR-M, ZCR-I, DURAT-I and MTOM-M are significant at the $p=0.005$ level.

The variable MTOM-M describes the dynamic range of the middle phase, but it is also influenced by the presence or absence of the final burst. When the presence or absence of the final burst is controlled, MTOM-M is not significantly dependent on asthma ($F=0.23$, $df=1$, $p<0.6$). In terms of asthmatic discrimination, MTOM-M really represents the presence or absence of the final burst.

The zero-crossing rate of both phases (ZCR-I and ZCR-M), which characterizes the dominant frequency component of the sound, is smaller for the asthmatics than for the controls. Note that the variables STDF-I and C1-I (which have some discriminating ability) are correlated with ZCR-I, as are MF-M and C1-M with ZCR-M (table 2). The better performances of ZCR-I and ZCR-M in the discrimination tests suggests that they can be measured more consistently than the other variables, which are all obtained from the cough spectrum (compare the standard deviations of ZCR-M and MF-M in table 3). Variables such as the central moments or cepstral coefficients depend on the entire spectral shape, so are affected by noise more than the zero-crossing rates.

It is interesting that the duration of the initial burst (DURAT-I) is significantly shorter for asthmatic coughs. Piirila and Sovijarvi [8] found that the cough sound duration was longer for asthmatic coughs than for coughs in other respiratory illnesses. Note, however, that they examined sequences of (spontaneous) cough sounds, whereas we analysed single (voluntary) coughs. Their "first cough sound" is therefore equivalent to our entire cough sound. The total duration of our cough sounds (TOTDURAT) did not differ significantly between the asthmatic and non-asthmatic groups.

The cough flow rates correlate very significantly to the peak flows obtained from forced expiratory manoeuvres. As shown in figure 3, peak flows equivalent to those in the forced expiratory manoeuvre are achieved. These results accord with those of previous studies [18], implying some equivalence between the airflow mechanics of the two manoeuvres (note, however, the greater variance of our cough flows compared to the PEFR, and the differences in flow limiting behaviour between the two manoeuvres observed by Beardsmore *et al.* [18]).

Although several of the cough sound variables correlated with the cough flow variables, these were not necessarily the variables that discriminated asthmatics from normals. In addition, plots of these variables against the flows reveal a wide scatter. Of course, to obtain a better relationship between cough flow and the sound characteristics, it is necessary to ensure that the subjects are more uniform than our mixed group of asthmatics and controls of different ages.

The pre-exercise to post-exercise changes in the feature variables are (individually) significantly different between the asthmatic and non-asthmatic groups for only a few of the variables examined. Only ZCR-M and SKF-M differ over several of the time slots (and the inclusion of SKF-M may be artefactual, since it differs only for the normals). One reason why so few variables change significantly after exercise is that the random variations in the pre-exercise and post-exercise coughs are added together, thus increasing the variance in the group. This is exacerbated by the small number of coughs used here. One way to reduce the variance of the pre-exercise to post-exercise differences would be to collect several coughs from each subject both before and after exercise. An "average" cough can then be obtained at each post-exercise time, whilst at the same time any gross outliers can be excluded from the ensemble. An initial trial of this approach, with 20 coughs collected from one subject, indicated that the coughs seem to form a fairly consistent group, with a few outliers corresponding to anomalous coughs.

Because several of the variables are uncorrelated with each other, a multidimensional approach is necessary to take account of each variable in the classification of the two groups. We employed a discriminant technique in which a multivariate normal distribution is assumed for each of the groups over the variables in the model. Each observation is classified as belonging to the group mean to which it is closest. This approach places equal importance on each of the variables incorporated in the model. This means that time-domain (such as DURAT-I) and frequency domain (such as ZCR-I) variables are treated in the same way. Because cough sounds can be regarded as a temporal sequence of spectral patterns (*i.e.* several "phases", each with a different spectral structure), it would probably be better to employ a classification technique in which the temporal structure is made more explicit. This view is reinforced by our results which reveal several significant variables

describing the temporal structure (notably DURAT-I and the presence or absence of a final burst). It may be that some of the techniques that are employed in speech recognition, such as hidden Markov modelling [19], would be suited to this task. The use of such techniques would eliminate the need to divide coughs into a fixed arbitrary number of phases.

Overall, from the various discrimination tests performed, the variables which seem "best" at distinguishing between asthmatic and non-asthmatic groups include DURAT-I, the presence/absence of a final burst, ZCR-I, ZCR-M, and the cepstral coefficients. The first two of these refer to the cough's temporal structure, the next two (ZCR-I and ZCR-M) to the dominant frequency component of the first two phases of the cough sound, whilst the cepstral coefficients are a multidimensional representation of the spectral shape.

The recognition error rate for the discriminant analysis ranges from 35% to <20%, although the results indicate that the asthmatic and non-asthmatic groups overlap considerably. Nevertheless, our results show significant differences between asthmatic and non-asthmatic coughs, both in themselves and in their responses to exercise induced asthma.

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