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TECHNICAL NOTE

Diagnostic potential in state space parameters of lung sounds

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Abstract The goal of this study was to investigate state space parameters of the lung sounds of healthy subjects and subjects with symptoms of asthma under different respiratory conditions. Our main objective was to elucidate the diagnostic potential of these parameters, which included embedding dimension (m), time delay (τ) and Lyapunov exponents (λ). Lung sounds were acquired over the right lower lobe from six healthy subjects, ages 10–26 years, and from eight children with symptoms of asthma recorded pre- and post-bronchial provocation via methacholine challenge (MCh) and post-bronchial dilation (BD). Inspiratory air flows during recordings were 7.5, 15, or 22.5 mL/s per kg (±20%). With increasing flow for sounds recorded from healthy subjects, mean values of τ decreased. Percent of breaths with positive λ decreased when heart sounds were excluded. For the patients who exhibited bronchoconstriction, values of τ increased and percent of positive λ decreased post-MCh, and returned to pre-MCh values post-BD. Thus, both τ and presence of positive λ may prove valuable in developing a model that will predict changes in respiratory status using lung sounds.

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1 Introduction

Recording lung sounds does not require the same degree of subject cooperation or physical capability as standard methods of pulmonary function testing (PFT), such as spirometry. Considering the diagnosis of airway hyperresponsivity or asthma, decrease in intensity of lung sounds has been found to accompany induced bronchial narrowing, and more consistently than wheeze [7, 19]. However, objective measurement of changes in lung sounds without adventitious sounds generally necessitates at least two recordings, e.g. at baseline and also post-bronchial narrowing. This need could be eliminated via a theoretical model of lung sounds. Such a deterministic model is within reach [17] but not yet in use. Without such a model, state space reconstruction from time series [1] offers a means of describing a dynamical system in terms of its structure and behavior, i.e. number of equations and expenditure of energy respectively. The state space contains the outputs of a dynamical system plotted with respect to one another.

Geometrical and dynamical state space parameters have been determined for lung sounds in healthy subjects in very few studies [3, 10, 16]. These invariants have shown promise as useful tools in the analysis of respiratory condition via lung sounds [3, 16]. With respect to other bioacoustic signals, classification of swallowing sounds between healthy and dysphagic subjects exhibited an accuracy of 83% when a geometrical state space invariant, the time delay, was used as a classification feature [2]. Reconstructed state spaces of speech sounds were useful in characterization of vowels, and a method of synthesizing these sounds was developed based on the Lyapunov exponent, which is a dynamical state space measure [6].

This study investigated geometrical and dynamical state space parameters of the lung sounds of healthy subjects and subjects with symptoms of asthma undergoing induced bronchoconstriction via methacholine challenge (MCh). The main objective was to elucidate the diagnostic potential of these parameters. Differences in parameters between healthy subjects and patients, and between patients pre-MCh, post-MCh, and post-bronchial dilation (BD) were examined. Effects of flow and presence of heart sounds were also assessed in healthy subjects. Heart sounds can affect lung sounds below 300 Hz [13].

2 Methods

2.1 Data recording and protocol

Previously recorded lung sounds from six healthy subjects (3 males) aged 10–26 years [13] and eight children undergoing MCh [14] were used in this study. Recordings from 8 (of 11) children (5 males) in whom pattern and amplitude of respiratory air flow did not change substantially between pre- and post-MCh and post-BD lung sound recordings were selected for this analysis. Lung sounds from all subjects had been acquired over the right lower lobe (RLL) posteriorly. For healthy subjects, air flow was measured while these subjects breathed at targets of 7.5, 15, and 22.5 mL/s per kg (± 20%) through a mouthpiece and pneumotach with a nose clip in place. One lung sound recording was obtained per target flow.

Lung sounds from the eight children with suspected asthma were obtained pre- and post-MCh. In four children with significant bronchial narrowing following MCh (responders), indicated by a greater than 20% decrease in forced expiratory volume in 1 s (ΔFEV_1), lung sounds were also recorded post-BD (salbutamol inhalation). Subjects breathed through a facemask and pneumotach at their spontaneous tidal flows, which were 15 mL/s per kg for the four responders and two of the non-responders, and 7.5 mL/s per kg for the other two non-responders.

In both studies [13, 14] lung sounds had been recorded in a quiet environment with accelerometers (Siemens EMT25C) that were taped to the skin with double-sided tape. Each recording was 50–60 s long. Signal conditioning was also the same between the two data sets: filtering via eighth order analog Butterworth filters with passband 7.5–2,500 Hz, and digitization at 10,240 Hz and 12-bits.

2.2 Data analysis

State space analyses were applied to lung sounds corresponding to inspiratory plateau flow (consistent across one recording) to avoid non-stationarities in the signals [3]. Data were analyzed with heart sounds included and also after their manual exclusion (located on spectrogram and via listening). Removal of segments containing heart sounds effectively shortened regions of inspiratory lung sounds at the flow plateau in some breaths, i.e., data preceding and following a heart sound were not connected.

Embedding dimensions [1] and time delay values [21] were determined to obtain the state space geometry via Takens method of delays [1]. This method provides a matrix of vectors that collectively form a multi-dimensional state space trajectory. The matrix contains an original time series and several delayed versions of itself. The time delay, τ, sets the initial length of the delay (applied to every sample of the time series). The embedding dimension, m, dictates the number of delayed time series to be formed, with each new version delayed by $n\tau$, $n = 1, 2,\ldots, (m-1)$. The relation between m and system dimension, M, is such that $m \geq 2M + 1$ [6]. Each row of the Takens matrix is a vector that defines a point in the reconstructed state space.

Past work provides further detail on techniques used to find the Takens matrix [16]. To summarize, the first step is to approximate τ by the lag at which the autocorrelation of the time series drops to ($1-1/e$; e is the numerical constant 2.71828…) of its maximum value [1]. Estimates of m were then found using the method of false nearest neighbors [1, 16]. Once m has been approximated, a scheme for determining an appropriate τ other than the autocorrelation method may be used, which involves finding the average displacement of the state space vectors from the identity line [21]. As τ increases, the displacement also increases, and the relationship is roughly linear until it begins to plateau. The optimal value of τ corresponds to the point at which the slope of the plateau is 40% of the slope of the linear increase [21].

From the state spaces of lung sounds per breath, Lyapunov exponents, λ_i ($i = 1, 2,\ldots, m$), were calculated [5, 16]. Lyapunov exponents were originally developed in classical mechanics to examine a system's stability, and the signs of exponents, i.e. positive or negative, provide indication of divergence or convergence (respectively) of a system's energy [5]. The presence of both positive and negative Lyapunov exponents provides evidence for existence of chaos [5], though a positive exponent may also mean the presence of a singularity [10, 24]. A method for determining Lyapunov exponents from time series-based state spaces [5] has been used successfully on speech signals [6], and has been applied to lung sounds in this study.

In particular, the percentages of breaths with positive λ_i values and of total positive λ_i values were used as features. Changes in these features implied changes in signal dynamics.

3 Results

Table 1 shows mean and standard deviation (SD) values of m, τ (in samples) based on [21], and the λ_i percentage features across the six healthy subjects for each target flow. For lung sounds of healthy subjects, whether including or excluding heart sounds, values of τ decreased with increasing flow. Embedding dimensions did not vary appreciably in any case. Figure 1 provides examples of graphs used in finding m, τ, and positive λ_i values for one breath at medium flow from one healthy subject, compared with lung sounds of one patient pre-MCh.

As shown in Table 1, the percentage of breaths with positive λ_i was the lowest at low flow, and also decreased with heart sound exclusion for every flow. The total percentage of positive relative to negative λ_i, also presented in Table 1, did not vary much between flows for lung sounds without heart sounds and increased with flow for lung sounds prior to exclusion of heart sound segments. On average at least two-thirds of λ_i were negative, for both healthy subjects and patients.

Noteworthy trends were exhibited for state space parameters of lung sounds acquired pre- and post-MCh and post-BD from responders, shown in Table 2. Percentage of breaths with positive λ_i and of total positive λ_i decreased post-MCh, and returned to near-pre-MCh values post-BD. The τ values behaved similarly, except they increased post-MCh rather than decreased. As found for healthy subjects, m values did not change appreciably.

Since lung sounds from the non-responders did not all match in terms of flow (i.e., two were acquired at 7.5 mL/s per kg while the others were acquired at 15 mL/s per kg as mentioned in Sect. 2), state space parameters were not averaged across these subjects. Values of m and τ for non-responders were not outside of the ranges found for other subjects (Tables 1, 2).

Interestingly, the percentage of total positive λ_i per responder and non-responder as a function of ΔFEV_1 (Fig. 2) fell by at least 10% post-MCh for subjects with ΔFEV_1 greater than or equal to 15% (magnitude), and did not appreciably change for non-responders with lower ΔFEV_1. It is important to note that though the non-responders did not exhibit a ΔFEV_1 that would warrant diagnosis of airway hyperreactivity (and potential diagnosis of asthma), they cannot be considered healthy, or even as control subjects for the responders to MCh, because they were referred by a physician for MCh due to symptoms suggesting asthma.

Figure 3 compares state space plots for the subjects used in Fig. 1. Embedding dimension vectors one and three, labeled X_1 and X_3, were used; since it is possible to plot at maximum only three dimensions, whereas there are m dimensions per breath, several combinations of vectors may be plotted with respect to one another, and X_1 and X_3 were thus chosen arbitrarily. The state space parameters describe the state space in detail, and provide more information than what can be manually observed; these graphs are shown only as typical examples of attractors.

4 Discussion

Mean values of the embedding dimension, m, changed little between flows for the lung sounds of healthy subjects. Values ranged between approximately 6 and 12; past work found values near both the lower [3] and the upper [10] bounds of this range based on lung sounds recorded over the left [3] and right and left [10] upper lung lobes anteriorly. Lung sounds in each of those studies were acquired with an electronic stethoscope and digitized at 44.1 kHz. Subjects breathed at about 15 mL/s per kg and lung sounds were analyzed within inspiratory flow at plateau in [3]. The values of m presented in [10] were not calculated but chosen and lung sounds were analyzed across both inspiration and expiration at tidal flow. The chosen values were said to be high in order to account for the possible presence of noise [10], which was inevitable due to the analysis of whole breaths.

Table 1 Mean ± SD of flow, m, τ from $\langle S_m(\tau)\rangle$, and percentage of breaths with positive λ_i and of total positive λ_i (healthy subjects)

Flow (L/s)	Including heart sounds				Excluding heart sounds			
	m	τ (samples)	Breaths with positive λ_i (%)	Total positive λ_i (%)	m	τ (samples)	Breaths with positive λ_i (%)	Total positive λ_i (%)
0.6 ± 0.1	8.0 ± 1.8	39.9 ± 20.1	78.8 ± 18.2	18.1 ± 6.73	8.8 ± 1.9	36.6 ± 15.5	65.3 ± 6.23	21.3 ± 4.95
1.1 ± 0.3	8.4 ± 1.5	34.4 ± 16.4	88.3 ± 13.4	26.5 ± 6.19	8.9 ± 1.6	30.5 ± 13.1	84.6 ± 19.9	26.8 ± 7.57
1.6 ± 0.3	8.5 ± 1.6	21.4 ± 15.7	91.5 ± 13.6	31.1 ± 5.05	9.9 ± 2.0	19.7 ± 11.6	76.4 ± 9.67	21.8 ± 6.52

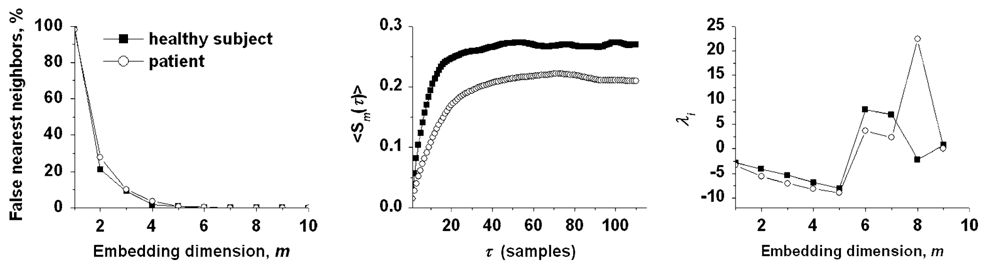

Fig. 1 State space measures for one healthy subject and one patient pre-MCh, based on one breath each (flow at 15 mL/s per kg, heart sounds excluded). Values of m and τ (in samples) chosen per these graphs were 10 and 18, respectively, for the healthy subject, and 8 and 34, respectively, for the patient

Table 2 Mean ± SD of flow, m, τ from $\langle S_m(\tau)\rangle$, and percentage of breaths with positive λ_i and of total positive λ_i (MCh responders) (flow = 15 mL/s per kg)

	m	τ (samples)	Breaths with positive λ_i(%)	Total positive λ_i(%)
Pre-MCh	9.2 ± 1.5	25.0 ± 7.4	96.4 ± 4.8	35.6 ± 2.7
Post-MCh	8.4 ± 1.3	31.7 ± 11.0	63.1 ± 27.6	18.7 ± 7.6
Post-BD	9.1 ± 1.3	24.0 ± 8.2	87.2 ± 7.6	32.3 ± 3.0

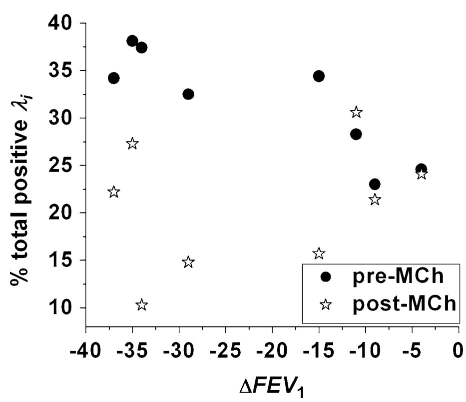

Fig. 2 Percentage of total positive λ_i as a function of ΔFEV_1 for all patients (lung sounds of the two subjects with ΔFEV_1 of –4 and –9% corresponded to flow of 7.5 mL/s per kg; others breathed at 15 mL/s per kg). The data points at ΔFEV_1 of –34% correspond to the patient shown in Fig. 1

Percentages of total positive and of breaths with positive Lyapunov exponents, λ_i, and values of time delay, τ, varied with flow in healthy subjects. These changes may represent the increase in turbulence that accompanies increase in flow, according to the Reynolds number [8]. Turbulence in itself has been shown to be chaotic [22], and this chaotic nature may be borne out by lung sounds at higher flows. Lung sound intensity increases with flow as well, and changes in λ_i and τ with flow may also be a result of this phenomenon. In order to definitively determine the extent to which the state space parameters found in this study were affected by sound intensity versus flow dynamics, more information pertaining to the latter would be required. Since it is not possible to visualize air flow within airways as a subject breathes, a physical model would help to elucidate how the parameters relate to sound intensity and flow, which is recommended for future study.

Considering flow dynamics, fewer occurrences of positive λ_i may indicate bronchial constriction, since decrease in airway diameter results in decrease in Reynolds number and hence reduction in turbulence [8]. Indeed, this result was found for the lung sounds of patients: percentages of breaths with positive λ_i and total percentages of positive λ_i substantially decreased post-MCh in responders, and were restored to near-pre-MCh values post-BD (Table 2). Past work with these data [14, 15] found that changes in sound intensity with bronchoconstriction did not have strong predictive value; thus, it is not unreasonable to postulate that properties of flow dynamics are preserved in the sound signal. Though there are changes that occur in the lungs with bronchoconstriction that could affect transmission of sound from airways to the chest wall, such as increased stiffness of airway walls and possible air trapping or hyperinflation, it is not clear which components of sound would be impacted by these factors.

Excluding heart sounds from lung sounds of healthy subjects also had an impact on the percentages of breaths with positive λ_i for all flow rates: the percentages decreased. The percentages of total positive λ_i decreased for high flow lung sounds and stayed approximately the same for low and medium flows. The results of state space analysis of heart sounds using the recurrence statistic reported in [4] complement the finding of our study. The recurrence statistic is related to the distance between state space vectors, and it was found to be lower for regions of lung sound recordings outside of heart sounds [4]. Decrease in this distance would theoretically be akin to increase in convergence of the attractor, which is represented by negative λ_i as mentioned in Sect. 2.

It is possible that the removal of the heart sound segments, rather than removal of heart sounds per se, could have caused the jumpy behavior of the percentage features (Table 1). While our team has developed several heart sound cancellation methods with minimum effect on the original lung sounds [11, 12, 20], we normally apply those techniques when the entire signal is needed for a physician to listen to the signal repeatedly, or in some cases such as acoustical flow estimation, we cancel the effect of heart sounds on the calculated feature, i.e., average power of the sound [23]. However, since any method of heart sound cancellation does change the segments including heart sounds slightly, for pilot studies in which we aim to investigate a new technique such as in this study, we prefer not to change the original signal at all; hence we only removed the segments including heart sounds. However, if this might have been one of the reasons for jumpy behavior of the percentage features, it should be investigated in a future study by applying heart sound cancellation methods.

Another contributing factor for jumpy behavior of percentage features could be that our data are not of infinite length, which is an ideal requirement of the Takens matrix [1], though the method we used to calculate λ_i was developed for short time series [5]. Using a higher sampling rate could have improved results [24]; note that our sampling rate was approximately 10 times higher than the high frequency content of our data.

The percentages of total positive λ_i for all cases indicate that there are many more negative than positive λ_i values, which is realistic because an overall energy dissipation (represented by negative λ_i) is expected [3, 5]. With heart sounds excluded, percentages of breaths with positive λ_i and of total positive λ_i for lung sounds of patients pre-MCh and post-BD were within the range of these percentages for lung sounds of healthy subjects for corresponding sensor location and flow (i.e., RLL and 15 mL/s per kg). This indicates that state space parameters may not be able to distinguish healthy lung sounds from lung sounds of subjects with hyperresponsive airways and possibly asthma. However, as mentioned above, it is encouraging that changes were exhibited in the state space parameters of patients' lung sounds between baseline and bronchial narrowing: percentages of positive λ_i decreased for all responders and one non-responder (who exhibited high ΔFEV_1) post-MCh (Fig. 2). Work of breathing increases with airway narrowing, partly due to hyperinflation, which causes an increase in pressure needed to generate flow, and partly because the diaphragms flatten, resulting in greater respiratory muscle effort [18]. Hence, energy dissipation in the respiratory system increases, and such energy behavior corresponds with negative λ_i values as indicated in Sect. 2, thus providing further justification for the λ_i results. Note that differing views exist on whether positive λ_i values for lung sound signals provide indication of chaotic dynamics [3] or singularities [10]; it is not an objective of our work to resolve the issue.

Values of τ for healthy subjects decreased with increase in flow for each sensor location whether heart sounds were present or not. These values did not change substantially with exclusion of heart sounds. On average, values of τ for the patients' lung sounds pre-MCh were slightly lower than those for corresponding healthy lung sounds, and increased post-MCh. This result is rather counter-intuitive to the observed decrease in percentages of positive λ_i discussed above. However, an explanation may be provided by examining Fig. 3, the surface area occupied by the trajectory appears to be more compact in the post-MCh example relative to pre-MCh, which agrees with the findings of λ_i suggesting convergence, but the points in the trajectory in

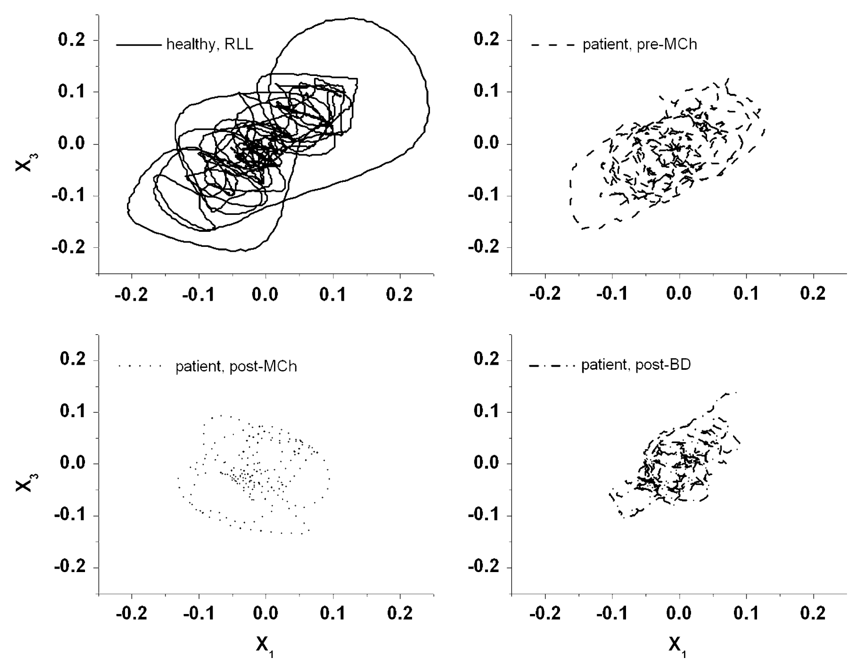

Fig. 3 Examples of state space trajectories for one healthy subject (**a**) and one patient pre-MCh (**b**), post-MCh (C), and post-BD (**d**) (*RLL* 15 mL/s per kg, heart sounds excluded)

this smaller space appear to be further apart, which would increase the distance measure in the method for finding τ [5, 16], and hence increase τ. It is important to recall, though, that the state space parameters account for all dimensions whereas any graphical presentation may display at most three.

Another important consideration is noise in the data. It has been suggested that state space analysis applied to data containing stochastic noise may result in parameters indicative of chaos when the data itself may not in fact be chaotic [9]. Separating the signals representing lung sounds from additive broad-band noise (which can result from a myriad of potential factors) would not be possible for the data employed in this work, because reference recordings of ambient sound during breathing or sound within the hardware were not acquired. This is a recommendation for future study. Though filtering data reduces noise to an extent, filtering should be avoided in state space analysis as it could alter the dynamics in the time series [24]. However, filtering is generally a necessity in order to satisfy the Nyquist criterion. Note that a sensor may in itself effectively filter data due to its particular frequency response.

Turbulence and vortical flow of air in ducts such as human airways produces sound, and equations governing this phenomenon in general are known [8]. Lung sounds are modified as a result of the passage of sound waves through the chest. Although highly complex, it is possible that as a whole the system producing lung sounds may be mathematically modeled [17]. The results of this study suggest that τ and λ_i values may prove constructive in modeling lung sounds. The consistency of m indicates that the number of differential equations involved in a system model would not change with conditions, e.g. air flow or respiratory status, implying that only model parameters would differ. As well, changes in both τ and λ_i may prove useful in classification of respiratory status, especially considering that the τ and percentages of λ_i values returned to pre-MCh values post-BD in responders to MCh. Unlike past analysis of state space parameters of lung sounds [3, 10], our work examined lung sounds acquired at different flows from healthy subjects and also lung sounds recorded from patients undergoing MCh. Further study with a larger, more uniform group of subjects, and with more information pertaining to flow dynamics (e.g. via a physical model), is required to verify the diagnostic potential of state space parameters in lung sound analysis.

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