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A Study of IOS Data Using the aRIC+I_p Model of Respiratory Impedance

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Abstract—Development of better methods to assess human lung function has been continuing since the existing standard lung function test of spirometry requires subjects to inhale and exhale with maximum effort, which may be troublesome especially for the elderly and young children, leading to unreliable results. Therefore, the method of forced oscillation, and the Impulse Oscillometry System (IOS) in particular, has been developed to lessen the effort of the patients while obtaining valid measurements. The applied pressure waves and the resulting airflow responses are recorded to provide information about the respiratory system's input impedance, which can be fit by electric circuit models to possibly serve as a means to detect and diagnose respiratory diseases. Presently, research continues to find a more accurate model that also provides reasonable component values. This paper proposes the augmented RIC+I_p (aRIC+I_p) model and compares it to five other well-known models (the RIC, extended RIC, augmented RIC, DuBois and Mead models) in fitting the IOS data from adult COPD patients and healthy subjects. While the aRIC+I_p model yielded slightly higher fitting error than the Mead and DuBois models, it did not produce unphysiologically large values for any of its components, unlike the Mead and DuBois models. Hence, the aRIC+I_p model appears to be the most reasonable one for use, at this point in time, in studying IOS-based computer-aided detection and diagnosis of COPD.

Keywords—Respiratory impedance, respiratory system model, parameter estimation, COPD

I. Introduction

For some time now, researchers have been seeking better ways to assess human lung function than the standard method of spirometric testing. During spirometry, subjects must attempt to inhale and exhale with maximum effort in order to produce technically acceptable measurements, which is physically demanding and requires their active cooperation. One alternative to spirometry is the method of forced oscillation, and the Impulse Oscillometry System (IOS) in particular, which requires only the subject's passive cooperation. This method allows them to breathe normally, although possibly with a nose clip to close the nares. Brief 40ms electrical pulses, producing 60-70 ms mechanical displacements of the speaker cone, result in pressure waves from the mouth inwards being superimposed on normal respiratory airflow into the lungs. Both the pressure stimulus and the resulting airflow response are recorded to provide information about the respiratory system's forced oscillatory impedance that can be used to detect and diagnose respiratory diseases. The resistive and reactive (Z_R and Z_X) impedance values that are calculated depend on the respiratory system's 'mechanical' resistances, compliances and inertances, so they can also be correlated with models consisting of electrical components that are analogous to those 'mechanical' components. Then parameter estimates for such models may provide an improved means of detecting and diagnosing respiratory diseases.

Presently, research is ongoing to find better models with lower errors in modeling IOS impedance data that also provide reasonable component values. In this paper, we propose the augmented RIC with peripheral inertance (aRIC+I_p) model and compare its performance in fitting the IOS data from adult COPD patients and healthy subjects to that of five other well-known models: the RIC, extended RIC, augmented RIC, DuBois and Mead models.

II. Respiratory Impedance Models

Of these five well-known models, the RIC, DuBois and Mead models have been studied considerably [1, 2, 3, 4]. More recently, the extended RIC (eRIC) [5] and augmented RIC (aRIC) models [6] have been proposed as improvements of the RIC model. The relationships among the models are illustrated in the model family tree of Fig. 1, which will be clarified when one understands what components make up each model.

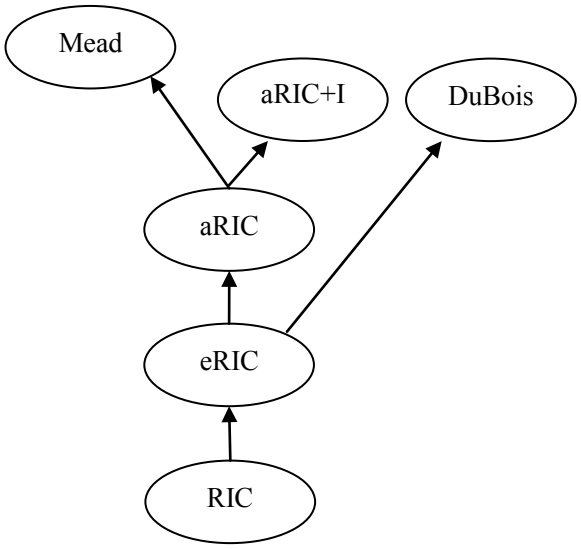

Fig. 1. Family tree of models

RIC model: It is the simplest model with only three elements: airway resistance R, air inertance I and lung compliance C, with units of R in $cmH_2O/L/s$ or $kPa/L/s$, I in $cmH_2O/L/s^2$ or $kPa/L/s^2$, and C in L/cmH_2O or L/kPa. Its diagram and impedance are given in [1].

Extended RIC model: This four-element model adds a peripheral resistance R_p in parallel with the compliance C of the RIC model to allow for the frequency dependence observed in typical real impedance data, which is beyond the RIC model's capability [5]. The extended RIC model's diagram and impedance are given in [5].

Augmented RIC model: This model was proposed as an improvement of the extended RIC model [6]. The additional element C_e (see Fig. 2) is intended to model extrathoracic compliance, which is thought to increase the real part of the respiratory system's impedance at the higher frequencies due to upper airways shunt effects, as observed in a significant proportion of IOS data. Such an upturn at the higher frequencies cannot occur with the extended RIC model [5], which accounts for its poorer modeling performance in these cases. Alternatively, the augmented RIC model can be regarded as a simplification of the Mead model (with C_l and C_w, as defined below, equal to infinity). Its impedance expression is given in [6].

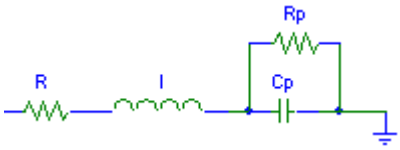

Fig. 2. Augmented RIC model

Mead model: This model is the most complex one among the six models being studied in this paper with seven parameters simulating different mechanics in the respiratory system [1, 3, 4]. Its components are: inertance (I), central and peripheral resistances (R_c and R_p), and lung, chest wall, bronchial, and extrathoracic compliances (C_l, C_w, C_b, C_e), as shown in Fig. 3. The Mead model's impedance is given in [1].

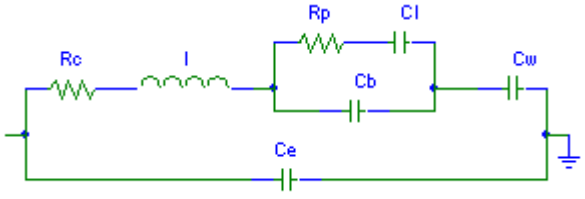

Fig. 3. Mead model

DuBois model In this six-component model proposed by DuBois *et al*. [2] the airway, tissue, and alveolar properties of the lung are divided into two different compartments. The parameters are airway and tissue resistance (R_{aw}, R_t), airway and tissue inertance (I_{aw}, I_t), and tissue and alveolar compliance (C_t, C_g)

Augmented RIC+I_p model: The aRIC+Ip model subsumes the RIC, eRIC and aRIC models. Its six components represent central and peripheral resistances (R, R_p), large airway inertance (I), small airway and extrathoracic compliances (C_p, C_e), as for the aRIC model, as well as an additional peripheral inertance (I_p): see Fig. 4. We have derived the impedance expression for this model, but do not present it here for space reasons.

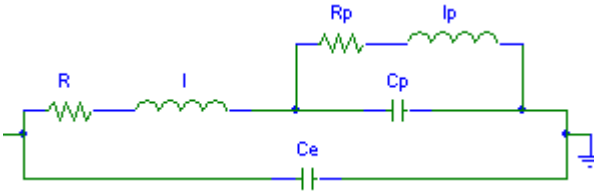

Fig. 4. Augmented RIC+I_p model

III. IOS Data

The first set of IOS data (Z_R and Z_X values at 5, 10, 15, 20, 25, 35 Hz) were obtained from 10 adults diagnosed with COPD: 1 female and 9 males, 54 – 79 years of age (mean 66 years, standard deviation (SD) 7.4 years), 1.60 – 1.80 m in height (mean 1.74 m, SD 5.6 cm), and weighing 54.5 – 95.9 kg (mean 79.0 kg, SD 11.5 kg). The second IOS dataset was obtained from another 10 adults with no identifiable respiratory disease: 3 females and 7 males, 24 – 67 years of age (mean 43.6 years, SD 14 years), 1.73 – 1.83 m in height (mean 1.77 m, SD 3.6 cm), and weighing 50.0 – 100.9 kg (mean 77.7 kg, SD 14.9 kg).

IV. Model Parameter Estimation

The fitting of models to given data was done via a process of selecting the model's component values (its parameters) known as parameter estimation. Similar to curve-fitting, parameter estimation minimizes a suitable error criterion

$$E = g\{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\} \qquad (1)$$

where $f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})$ are functions involving the n-vector $\mathbf{x}$ of parameters $x_1, x_2, \ldots, x_n$ and the independent variables, e.g., frequency of the m data samples [7]. The least squares (LS) criterion is by far the most commonly used for curve fitting and parameter estimation. In its generalized form, the LS criterion

$$\min\left[E = \sum_{i=1}^{m} \{w_i f_i(\mathbf{x})\}^2\right] \qquad (2)$$

minimizes the weighted (by w_i) sum of the squared errors (differences from the m data samples). It was chosen for

this work due to its commonplace use, its relationship with other system identification algorithms and its availability in different software packages.

A gradient-based linear LS algorithm and a nonlinear LS algorithm were used for estimating the parameters of the above models – with Z_R and Z_X weighted equally. The former algorithm could be applied to the simpler 3-element RIC model, but the latter was necessary for the other models whose impedance functions depend nonlinearly on the parameters. However, the nonlinear LS algorithm – unlike the linear LS algorithm – does not always produce parameter estimates corresponding to a global error minimum. Instead, the estimates it obtains may correspond to just local minima. To address this issue, a procedure was employed in which for each and every estimation run (with at least 25 runs per test data), an initial parameter estimate vector was produced by a random number generator. Such a procedure increases the likelihood that the algorithm converges to parameter estimates corresponding to a global error minimum.

V. Results and Discussion

Table 1 shows the mean least squares error in fitting Z_R, the mean least squares error in fitting Z_X, the mean LS error in fitting Z (defined as the sum of the mean Z_R and Z_X least squares errors) and standard deviation of the LS error in Z, achieved by each model for parameter estimation performed on all the COPD patients' data.

Table 1. Mean modeling errors for COPD patients (25 tests)

Model	Mean Z_R LS error	Mean Z_X LS error	Mean Z LS error	Z LS error std dev
RIC	0.02368	0.00379	0.02747	0.02868
eRIC	0.00111	0.00290	0.00401	0.00279
aRIC	0.00064	0.00070	0.00134	0.00087
aRIC+Ip	0.00061	0.00063	0.00124	0.00090
DuBois	0.00060	0.00051	0.00111	0.00073
Mead	0.00037	0.00057	0.00095	0.00065

This table shows that the RIC model has the largest estimation error, due to its simple structure, followed by the eRIC and aRIC models (as expected from their structural relationships to each other), while the 7-element Mead model has the lowest error after the 6-element DuBois model. From this trend, it can be inferred that the fitting accuracy of each of these models is directly related to the complexity of its structure, *i.e.*, the number of elements it contains. However, other issues besides minimizing the error in curve fitting must be considered. Specifically, the Mead and DuBois models typically yielded unphysiologically large values as the optimal solution for some capacitances (C_l and C_w for the Mead model and C_t for DuBois model), the majority of those values being several orders of magnitude larger than the expected range of compliances: this unfavourable property of these two models had previously been established in [5, 6]. Prior to the aRIC+I_p model being studied, the aRIC model had been considered to be the most reasonable model to use for fitting IOS data [6]. But Table 1 shows that the aRIC+I_p model performs slightly better than the aRIC model for fitting COPD patients' data, while also producing physiologically reasonable values for all of its components.

Table 2 presents the mean modeling errors for the group of normal adult subjects. Note that the mean total errors of the six models are still ranked in the same order as for the COPD patients except that the aRIC model is now a better fit than the DuBois model and is only slightly worse than the Mead model. We hypothesize that this advantage over the DuBois mainly accrues from the presence of C_e in the aRIC model. However, note that the Mead and DuBois models again typically yielded unphysiologically large values for their C_l and C_w, and C_t, capacitances, respectively. On the other hand, the aRIC and aRIC+I_p models always produced physiologically reasonable values for all their components. And, quite significantly, the aRIC+I_p model also fit the normal adults' data slightly better than the Mead model.

Table 2. Mean modeling errors for normal adults (33 tests)

Model	Mean Z_R LS error	Mean Z_X LS error	Mean Z LS error	Z LS error std dev
RIC	0.00240	0.00059	0.00299	0.00155
eRIC	0.00169	0.00102	0.00271	0.00178
aRIC	0.00027	0.00036	0.00064	0.00062
aRIC+Ip	0.00023	0.00023	0.00046	0.00043
DuBois	0.00065	0.00024	0.00089	0.00070
Mead	0.00023	0.00035	0.00057	0.00063

It has been suggested that, in addition to data-fitting ability and physiological appropriateness of estimated parameters, statistical confidence in those estimates should be one of the main criteria to judge model appropriateness, assuming that errors between measured impedance and least-squares-optimized model impedance at various oscillation frequencies satisfy a zero-mean Gaussian distribution [8]. While we did not perform a formal analysis such as proposed in [8], we found that our estimation results for the Mead and DuBois models produced least-squares-optimized estimates (mostly of C_l but occasionally of C_w in the Mead and C_t in the DuBois models) that could vary by 2 to 3 orders of magnitude, *i.e.*, they typically produced multiple near-optimal solutions. On the other hand, the estimation results for the eRIC, aRIC and aRIC+I_p models produced precise, reliable optimal estimates for all their components.

VI. Conclusions

This paper has introduced the aRIC+I_p model and compared it to the RIC, extended RIC, augmented RIC, DuBois and Mead models in terms of how well their estimated impedances fit the IOS impedance data of adult COPD patients and healthy subjects, and of the reasonableness of their estimated component values. This new model yielded a lower error than all the other models except for the Mead and DuBois models (when fitting COPD data). But because those two models typically yielded unphysiologically large values for some of their capacitances, the aRIC+I_p model appears to be the most reasonable choice at present for use in IOS-based computer-aided detection and diagnosis of COPD.

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