A New Estimator to Minimize the Error Due to Breathing in the Measurement of Respiratory Impedance

DANIEL NAVAJAS, RAMÓN FARRÉ, MAR ROTGER, AND RENÉ PESLIN

Abstract—**This paper presents a new respiratory impedance estimator to minimize the error due to breathing. Its practical reliability was evaluated in a simulation using realistic signals. These signals were generated by superposing pressure and flow records obtained in two conditions: 1) when applying forced oscillation to a resistance-inertance-elastance (RIE) mechanical model; 2) when healthy subjects breathed through the unexcited forced oscillation generator. Impedances computed (4–32 Hz) from the simulated signals with the new estimator resulted in a mean value which was scarcely biased by the added breathing (errors less than 1 percent in the mean R, I, and E) and had a small variability (coefficients of variation of R, I, and E of 1.3, 3.5, and 9.6 percent, respectively). Our results suggest that the proposed estimator reduces the error in measurement of respiratory impedance without appreciable extracomputational cost.**

INTRODUCTION

THE MECHANICAL input impedance measured by forced excitation characterizes the dynamic behavior of the respiratory system. The technique is based on submitting the respiratory system to a small amplitude and wide-band air perturbation while the subject breathes spontaneously. Given the fact that the subject breathes against the measuring device during forced excitation, a pressure is generated at the mouth due to the nonzero mechanical impedance of this device. Thus, two mechanical generators (i.e., the forced excitation device and the respiratory system) act simultaneously [4]. Hence, at frequencies where the activity of both generators is significant, the forced excitation signals are contaminated by the noises associated with the spontaneous breathing of the subject. In this situation where the input and the output of the system are corrupted by noises that are mutually correlated, impedance estimates calculated from the recorded signals are biased if the conventional cross-spectrum input–output estimators are used [1], [3], [4]. To reduce the bias error, Daroczy and Hantos [3] proposed a different alternative by using the driving voltage of the excitation device as a third signal to compute respiratory impedance. This approach is not generally used in practice since three instead of two signals must be processed. Moreover, the method is based on the assumption that the conversion of the driving voltage into the excitation pressure in the forced excitation device is linear [3], [5].

In this paper, a new respiratory impedance estimator to eliminate the bias error due to the correlation between pressure and flow breathing is proposed. It is based on using the available knowledge concerning the relation of the pressure and flow noises from the impedance of the measuring device. No hypothesis concerning the voltage–pressure conversion is required. Moreover, this impedance estimator only requires the spectral estimation of the two usual recorded signals: pressure and flow. Thus, the computational time is not increased.

THEORY

Input respiratory impedance is estimated by forced excitation from pressure and flow recorded at the mouth. Fig. 1 shows a block diagram, in the frequency domain, of the signals involved. In this figure and the following, all signals are represented by their Fourier transforms. The dependence on frequency has been omitted to simplify the notation. $\dot{V}_e$ and P_e are the excitation flow and pressure signals. Z_{rs} is the input impedance of the respiratory system defined as follows:

$$Z_{rs} = \frac{P_e}{\dot{V}_e}. \tag{1}$$

$\dot{V}_b$ is the breathing flow and P_b is the corresponding pressure generated. P and $\dot{V}$ are the signals recorded by the transducers. P_b and $\dot{V}_b$ act as noise corrupting the excitation signals:

$$\dot{V} = \dot{V}_e + \dot{V}_b \tag{2}$$

$$P = P_e + P_b. \tag{3}$$

The pressure and flow breathing noises are related by means of the input impedance of the measuring device Z_e:

$$P_b = -Z_e \cdot \dot{V}_b. \tag{4}$$

The negative sign in (4) is due to the opposite placement of the measuring device and the respiratory system in relation to the direction of flow. Substituting for P_e and P_b from (1) and (4) in (3) yields

$$P = Z_{rs} \cdot \dot{V}_e - Z_e \cdot \dot{V}_b. \tag{5}$$

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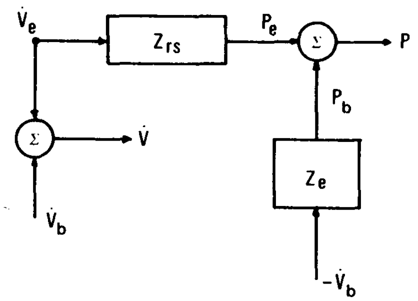

Fig. 1. Block diagram of excitation signals and noises.

Since $\dot{V}_e$ and P_e are not directly measurable, Z_{rs} is usually estimated from recorded $\dot{V}$ and P. The two estimators [6], [7] that are most widely used to calculate Z_{rs} are

$$Z_1 = \frac{P \cdot \dot{V}*}{\dot{V} \cdot \dot{V}*} = \frac{G_{pv}}{G_{vv}} \tag{6}$$

$$Z_2 = \frac{P \cdot P*}{\dot{V} \cdot P*} = \frac{G_{pp}}{G_{vp}} \tag{7}$$

where the superindex * indicates a complex conjugate and G_{xy} is defined as $X \cdot Y*$. Applying (2) and (5) and making the generally accepted assumption [4], [5] that the forced excitation and the breathing signals are uncorrelated, it follows that

$$Z_1 = \frac{Z_{rs} \cdot G_{veve} - Z_e \cdot G_{vbvb}}{G_{vbvb} \cdot G_{veve}} \tag{8}$$

$$Z_2 = \frac{Z_{rs} \cdot Z_{rs}^* \cdot G_{veve} + Z_e \cdot Z_e^* \cdot G_{vbvb}}{Z_{rs}^* \cdot G_{veve} - Z_e^* \cdot G_{vbvb}}. \tag{9}$$

Two major potential sources of error in Z_1 and Z_2 estimates arise. The first is a bias error due to the correlation between pressure and flow breathing noises [(4)]. Given that in conventional impedance measurements $Z_e \neq 0$ and $G_{vbvb} \neq 0$, the two estimators result in biased and different impedance estimates [(8) and (9)]. Moreover, as Z_1 and Z_2 depend on the value of G_{vbvb}, these biases are different for each subject and, thus cannot be corrected easily. If an ideal measuring device with $Z_e = 0$ was available, Z_2 would be unbiased ($Z_2 = Z_{rs}$) whereas Z_1 would still remain biased $[Z_1 = Z_{rs} \cdot G_{veve}/(G_{vbvb} + G_{veve})]$. The second source is the bias and random statistical sampling errors inherent in the finite length of the pressure and flow records available in practice. Hence, only estimates of the true value of auto- and cross-spectra can be used to compute Z_1 and Z_2.

When respiratory impedance is estimated by means of Z_1 or Z_2, one proceeds as if no information relating $\dot{V}_b$ and P_b was available. Although these breathing noises cannot be measured separately, we know the transfer function Z_e of the system connecting them. This physical information is included in (5). Deducing V_e from (2) and (5) gives

$$\dot{V}_e = \frac{Z_e \cdot \dot{V} + P}{Z_{rs} + Z_e}. \tag{10}$$

From (1), applying (2) and (3), and assuming that excitation and breathing signals are uncorrelated ($P_b \cdot \dot{V}_e^* = 0$; $\dot{V}_b \cdot \dot{V}_e^* = 0$), it follows that

$$Z_{rs} = \frac{P_e}{\dot{V}_e} = \frac{P_e \cdot \dot{V}_e^*}{\dot{V}_e \cdot \dot{V}_e^*} = \frac{P \cdot \dot{V}_e^* - P_b \cdot \dot{V}_e^*}{\dot{V} \cdot \dot{V}_e^* - \dot{V}_b \cdot \dot{V}_e^*} = \frac{P \cdot \dot{V}_e^*}{\dot{V} \cdot \dot{V}_e^*}. \tag{11}$$

Substituting for $\dot{V}_e$ from (10) yields

$$Z_{rs} = \frac{Z_e^* \cdot P \cdot \dot{V}* + P \cdot P*}{Z_e^* \cdot \dot{V} \cdot \dot{V}* + \dot{V} \cdot P*}. \tag{12}$$

Hence, we define a new estimator Z as follows:

$$Z = \frac{Z_e^* \cdot G_{pv} + G_{pp}}{Z_e^* \cdot G_{vv} + G_{vp}}. \tag{13}$$

To compute Z only one of the two cross-spectra has to be calculated in practice since $G_{vp} = G_{pv}^*$.

From (13), $Z = Z_{rs}$ provided that the true values for auto- and cross-spectra were used to compute Z. Consequently, the main source of bias error due to the correlation between pressure and flow breathing noises has been eliminated on estimator Z. Furthermore, only auto- and cross-spectra of the recorded pressure and flow signals are required to compute Z. Nevertheless, given that only records of finite length are available in practice to compute spectra, the potential source of bias and random statistical sampling errors remain. In order to evaluate the magnitude of these errors and the performance of Z in practical impedance measurements, we carried out a simulation study using realistic excitation and breathing signals.

Simulation

Material and Methods

We used a forced-excitation device similar to those described in the literature [3], [4]. It was based on a 12 in loudspeaker attached to a 8 l chamber. A bias tube connected to the chamber allowed the spontaneous breathing of the subject. Air in the device was renewed with a suction pump. The forced random noise excitation signal was generated by a microcomputer (IBM-PC/AT) and subsequently analogically low-pass filtered (0–32 Hz). Flow was recorded with a mesh-wire screen pneumotachograph and a differential pressure transducer (MP-45, Validyne, U.S.). Pressure was recorded with a similar transducer. Signals recorded by the transducers were analogically low-pass filtered (0–32 Hz) to prevent aliasing and digitized at 128 Hz. The mechanical impedance of the excitation device Z_e was measured by connecting a second loudspeaker to its outlet. The Z_e modulus was 1.01 hPa $\cdot$ l^{-1} $\cdot$ s at 4 Hz and decreased slightly with frequency down to 1.00 hPa $\cdot$ l^{-1} $\cdot$ s at 32 Hz. This value of Z_e is similar to others previously reported [4], [7].

We constructed a resistance-inertance-elastance (RIE) mechanical model by arranging in series a mesh-wire screen resistance, a rigid cylindrical tube and a rigid wall bottle. The impedance of this model was similar to that of a healthy subject (Table I). Forced excitation (± 1 hPa) was applied to the model. We obtained 16 different records (32 s each) of noise-free flow $\dot{V}_e$ and pressure P_e excitation signals. Breathing noises were obtained from 16 healthy young volunteers (5 male, 11 female). Their spirometric indexes were within the normal range. For each subject, we recorded 32 s of flow $\dot{V}_b$ and pressure P_b signals while the subject was spontaneously breathing through the measuring device, as in a real impedance test, but without applying any excitation signal to the loudspeaker. By adding one different $\dot{V}_e$ signal to each $\dot{V}_b$ noise, and similarly proceeding with the paired pressures, we synthesized 16 pairs of noisy pressure P and flow $\dot{V}$ records. In this way, we generated an ensemble of 16 pressure and flow samples which simulated recordings of 16 subjects with different breathing patterns but each one with a respiratory impedance equal to that of the model. A section of a representative pair of flow and pressure records is shown in Fig. 2.

Each of the 32 s long P and $\dot{V}$ synthesized records were digitally high-pass filtered (Butterworth, 3 poles, 3 dB at 2 Hz) and divided into 63 blocks of 1 s (with 50 percent overlapping). These blocks were multiplied by a Hanning window and fast Fourier transforms (FFT) were computed. Averaging over the 63 blocks, an ensemble of 16 sample estimates of auto- and cross-spectra were computed [1]. These estimates were used to calculate Z_1, Z_2 and Z [(6), (7), and (13)] and the corresponding coherence function γ^2 [1].

To evaluate the total bias and random error of each estimator, the mean value and standard deviation over the 16 values of Z, Z_1, and Z_2 were calculated. Finally, each obtained impedance curve was fitted to that of a RIE mathematical model by means of a standard least square algorithm [8]. Mean values and standard deviation of resistance, inertance, and elastance estimates were computed.

TABLE I
MEAN AND STANDARD DEVIATION OF THE PARAMETERS

	Z_{rs}	Z	Z_1	Z_2
R	2.32	2.32 ± 0.03 (1.3 percent)	2.16 ± 0.12 (5.5 percent)	2.37 ± 0.04 (1.7 percent)
I	1.14	1.15 ± 0.04 (3.5 percent)	1.07 ± 0.05 (4.7 percent)	1.27 ± 0.19 (15.0 percent)
E	53.0	53.2 ± 5.1 (9.6 percent)	44.3 ± 5.9 (13.3 percent)	68.5 ± 27.9 (40.7 percent)

Coefficients of variation in brackets. R, I, and E in hPa $\cdot$ l^{-1} $\cdot$ s, 10^{-2} $\cdot$ hPa $\cdot$ l^{-1} $\cdot$ s^2, and hPa $\cdot$ l^{-1}, respectively.

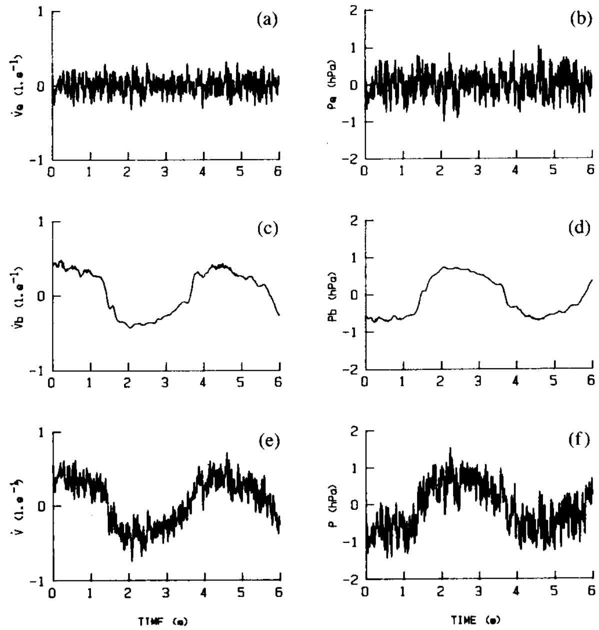

Fig. 2. Fragments of representative pairs of flow and pressure records used in the simulation. (a) and (b) flow ($\dot{V}_e$) and pressure (P_e) corresponding to the forced excitation. (c) and (d) flow ($\dot{V}_b$) and pressure (P_b) noises due to breathing. (e) and (f) noisy flow ($\dot{V}$) and pressure (P) data used to compute impedance.

RESULTS

For each estimator, Fig. 3 shows the mean value and the standard deviation of the real and imaginary parts of the computed impedances of the 16 samples. In this figure, the model impedance, in the following named Z_{rs}, is also shown for reference. Z_{rs} was calculated from the average of the auto- and cross-spectra of the 16 noise-free excitation records. With the proposed estimator Z [Fig. 3(a)], the mean impedance clearly approached Z_{rs}. Fig. 3(b) and (c) correspond to Z_1 and Z_2 for the same simulated noisy records. In accordance with (8) and (9) for low frequencies where breathing noise contamination (G_{vbvb}) was greater, the differences between the mean impedances and Z_{rs} were clearly greater than in Fig. 3(a). The real part of Z_{rs} was underestimated and its imaginary part was overestimated by Z_1 whereas the contrary behavior was found for Z_2. The differences between the mean values of the population and those of Z_{rs} were greater for Z_1 than for Z_2 in the real part and greater for Z_2 than for Z_1 in the imaginary part. The standard deviations increased considerably in relation to those of Z [Fig. 3(a)], especially in the case of Z_2.

The mean of the coherence function corresponding to the impedance estimates in Fig. 3 are depicted in Fig. 4. Up to around 12 Hz mean coherence increased with frequency. This was a consequence of the high-level of breathing noise contamination at the lowest frequencies. We obtained a mean value of G_{vbvb}/G_{veve} of 0.41 at 4 Hz where coherence was around 0.5. By contrast, at 12 Hz the mean value of G_{vbvb}/G_{veve} was 0.02 where mean coherence was 0.96.

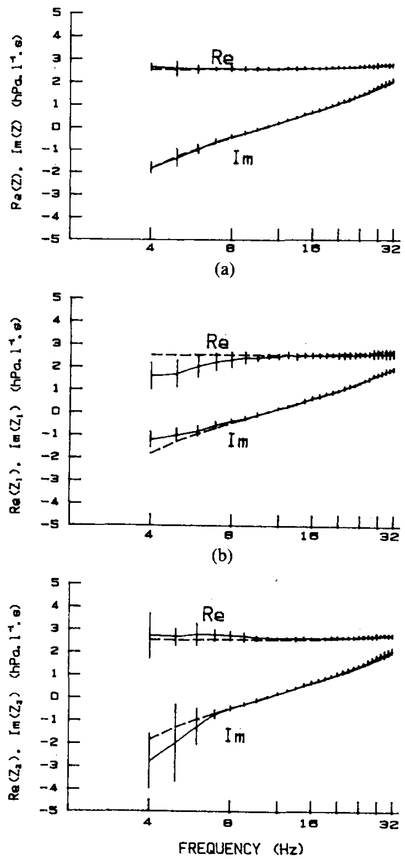

Fig. 3. Mean values and standard deviations of the real (Re) and imaginary (Im) parts of estimated impedances. Z_{rs} in dashed lines. (a) Z estimator, (b) Z_1 estimator, (c) Z_2 estimator.

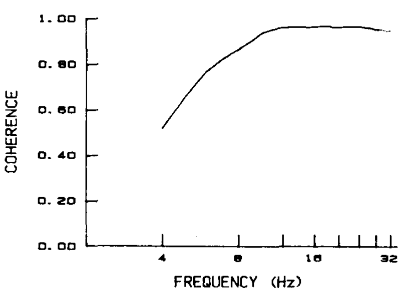

Fig. 4. Mean value of the coherence function between pressure and flow.

Parameter values in Table I quantifies the results shown in Fig. 3. This table shows the R, I, and E values fitted from Z_{rs}. It also shows the mean and standard deviation of the parameters fitted from the impedance estimates of Z, Z_1, and Z_2. For the Z estimator, the mean R, I, and E were close to those of Z_{rs} (differences of less than 1 percent) with coefficients of variation smaller than 2, 4, and 10 percent, respectively. By contrast, for the other estimators the mean R, I, and E parameters differed from true values (6.9, 6.1, and 16.4 percent for Z_1 and 2.2, 11.4, and 29.2 percent, for Z_2, respectively) and the coefficients of variation of the parameters clearly increased with respect to those of Z.

Discussion

The estimator Z proposed in this work was specifically designed to be applied to measurements of input respiratory impedance. It was defined from the equations linking the characteristics of the respiratory and measuring sytems (Z_{rs} and Z_e) with the excitation and breathing noise signals. In the theoretical approach followed to define Z, no special hypothesis has been made concerning the spectral characteristics of the forced excitation signal. Therefore, the proposed estimator can be used for any kind of excitation: random, pseudorandom, or sinusoidal. The hypothesis of uncorrelation between excitation and breathing is generally accepted [4], [5]. Furthermore, it was indirectly verified by Franken *et al.* [5] when the excitation signal was pseudorandom (2, 4, 6, $\cdots$, 32 Hz). As the mechanical impedance of the measuring device Z_e is involved in the definition of Z [(13)], it is assumed that Z_e is constant when the device is submitted to the spontaneous breathing flow. This requirement, which is also implicitly assumed in the approach of Daroczy and Hantos [3], may be easily met by an adequate design of the excitation device. In contrast with the indirect estimation proposed by Daróczy and Hantos [3], no hypothesis concerning the linearity of the transformation of loudspeaker driving voltage to chamber pressure was required to define Z.

The performed simulation gave estimates of the expected value and variance when the impedance of a model was calculated from realistic noisy signals with a duration similar to those of usual impedance measurements. The simulation was carried out with a simple RIE stationary model since it is widely used to interpret respiratory impedance data of healthy subjects [5], [6]. Moreover, the impedance of this model is easily parametrized in terms of R, I, and E by means of a linear procedure [8]. Nevertheless, as the theoretical unbiasness of Z does not depend on the particular model used in a further analysis of the measured respiratory impedance, Z may be applied when more complex models are used to fit experimental data. For instance, in the case of multicompartmental models, including partitioning of airways, alveolar gas, and chest wall. The results obtained showed that the estimator Z was scarcely affected by the statistical sampling errors arising from the use of auto- and cross-spectral estimates obtained from short records of signals. As was expected from its definition, Z showed a mean value which was scarcely biased even for mean coherences as low as 0.5. By contrast, Z_1 and Z_2 resulted in values that were clearly biased, according to (8) and (9), and to the results reported by Daroczy and Hantos [3]. Moreover, the standard deviations of the estimated impedances (and also of the fitted parameters) were clearly smaller for Z than for the other two estimators. This was also expected since Z

was defined to be unaffected by the breathing noises whereas Z_1 and Z_2 were not. The standard deviations of these two later estimators were due to the errors associated with the spectral estimates and to the variability of G_{vbvb}. For the population of healthy subjects studied in this work, we found that the coefficients of variation of G_{vbvb} were around 100 percent at all frequencies. Furthermore, the improvement in impedance estimation observed in Fig. 3 and in Table I was achieved with the same cost of spectral estimation (FFT) since Z only requires processing of the P and $\dot{V}$ records.

The signal-to-noise ratio depends on the energy of the spontaneous breathing flow of each subject and on the energy of the forced excitation signal which cannot be arbitrarily increased. At low frequencies where the breathing energy is great, only low signal-to-noise ratios may be achieved during forced excitation, especially in patients [2]. Thus, if a biased estimator is used, impedance measurements may become useless even when prolonging the measuring time since increasing the signal length would only reduce random errors but not bias [4], [5]. In contrast, the calculation of Z from signal records that are sufficiently long to reduce random errors would provide a reliable impedance estimation for low values of the signal-to-noise ratio. The prolongation of the measuring time is not difficult to carry out in clinical practice since patient fatigue may be avoided by allowing pauses between forced excitation recordings. Our simulation study suggests that the use of the Z estimator could extend the frequency range of reliable measurements to lower frequencies, thus providing more physiological and clinical information from respiratory impedance tests.

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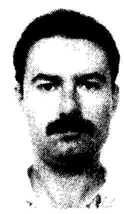

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