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Comparison of six models of the respiratory system based on parametric estimates from three identification models

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Abstract

The identification of respiratory impedance based on mathematical models and the consequent assessment of respiratory work propose an aid to adequately setting ventilatory support. We compared the respiratory models RC, RIC, eRC, eRIC, aRC and aRIC using parametric identification by ARX, ARMAX and OE and data from simulations, volunteers and patients. The comparison bases on the quality of the estimation and of the reconstruction of the output pressure signal representing the inspiratory effort.

1 Introduction

Non-invasive support ventilation is for many patients suffering from pulmonary insufficiency an effective treatment, especially in home care. Proper modelling of their respiratory system may offer a deeper understanding on its properties and promote the adequate adaptation of support. Finding the set of parameters that best describe the system conduces to a reconstruction of the applied muscular pressure, obtaining a continuous assessment of the patient's respiratory work.

2 Methods

The best known model, the RC-model, describes the respiratory system by its resistance (R) and its compliance (C). When inertial forces are considered, the inertance (I) is included, building the RIC-model. The extended RIC-model (eRIC) [1] adds a peripheral resistance (Rp) in parallel to the compliance C. The augmented RIC-model (aRIC) [2] contains in addition the extra-thoracic compliance (Ce) in parallel to the eRIC. When the frequencies of the signals are low (<1Hz), as during assisted spontaneous breathing, the inertial effects can be neglected and the parameter I disappears leading to the extended-RC (eRC) and augmented-RC (aRC) models.

The model parameters can be found by parametric identification using the models ARX, ARMAX and OE, which describe real systems with the structure shown in image 1 and differ from each other basically in the way how stochastic inputs like noise are modelled and in the algorithms used for estimation.

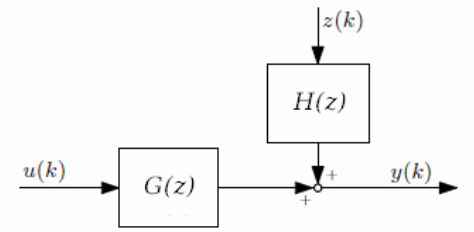

Image 1 General structure of a real system

The transfer function *G(z)* represents the total impedance Z of the respiratory system. The input *u(k)* corresponds to the flow (V') and the output *y(k)* to the sum of airway pressure (Paw) and transdiaphragmatic pressure (Pdi). The effect of disturbances *z(k)* is modelled according to the transfer function *H(z)*.

In this study, the respiratory signals were gained first from simulations and then from measurements with 3 volunteers and 3 patients. Pdi offers currently the best approximation to the real respiratory work and was therefore measured using balloon tipped catheters, to obtain Pdi as the difference of pressures between oesophagus and stomach [3]. Note that this standard procedure only serves for the analysis of models to be used parallel in the development of non-invasive methods.

Independent of the way of identification, the total impedance can be calculated for each model as Z= (Paw+Pdi)/V' and written in Laplace form for each model as follows:

$$G_{RC}(s) = \frac{1 + s\,RC}{s\,C}$$

$$G_{RIC}(s) = R + sI + \frac{1}{sC}$$

$$G_{eRC}(s) = \frac{sCpRRp + R + Rp}{sCpRp + 1}$$

$$G_{eRIC}(s) = \frac{s^2 CpIRp + s(CpRRp + 1) + R + Rp}{sCpRp + 1}$$

$$G_{aRC}(s) = \frac{R + Rp + sRRpCp}{1 + s(RCe + RpCe + RpCp) + s^2(RRpCeCp)}$$

$$G_{aRC}(s) = \frac{R + Rp + s(RRpCp + I) + s^2 IRpCp}{1 + sA + s^2(RRpCeCp + CeI) + s^3(IRpCeCp)}$$

with $A = (RCe + RpCe + RpCp)$

For the analysis of discrete systems the z-transformation is used turning *G(s)* into *G(z)* with the general form

$$G(z) = \frac{b_0 + b_1 z^{-1} + \ldots + b_m z^{-m}}{1 + a_1 z^{-1} + \ldots + a_n z^{-n}}$$

A least squares fit finds the coefficients a_0 to a_n and b_0 to b_m, which are related to the model parameters as follows.

For the RC-model:

$$b_0 = \frac{T + RC}{C} \quad b_1 = -R \quad a_1 = -1$$

For the RIC-model:

$$b_0 = R + \frac{I}{T} + \frac{T}{C} \quad b_1 = -\left(R + \frac{2I}{T}\right) \quad b_2 = \frac{I}{T} \quad a_1 = -1$$

For the eRC-model:

$$b_0 = \frac{CpRRp + RT + RpT}{CpRp + T}$$

$$b_1 = -\frac{CpRRp}{CpRp + T} \quad a_1 = -\frac{CpRp}{CpRp + T}$$

For the eRIC-model:

$$b_0 = \frac{CpRRp + ICpRp\frac{1}{T} + I + RT + RpT}{CpRp + T}$$

$$b_1 = -\frac{CpRRp + I + 2CpIRp\frac{1}{T}}{CpRp + T}$$

$$b_2 = \frac{ICpRp\frac{1}{T}}{CpRp + T} \quad a_1 = -\frac{CpRp}{CpRp + T}$$

For the aRC-model:

$$b_0 = \frac{T(TR + TRp + RRpCp)}{k_{aRC}} \quad b_1 = -\frac{TRRpCp}{k_{aRC}}$$

$$a_1 = -\frac{TRCe + TRpCe + TRpCp + 2RRpCpCe}{k_{aRC}}$$

$$a_2 = \frac{RRpCpCe}{k_{aRC}}$$

with

$$k_{aRC} = T^2 + TRCe + TRpCe + TRpCp + RRpCpCe$$

And for the aRIC-model:

$$b_0 = \frac{T^3(R + Rp) + T^2(RRpCp + I) + TRpICp}{k_{aRIC}}$$

$$b_1 = -\frac{T^2(RRpCp + I) + 2TRpICp}{k_{aRIC}} \quad b_2 = \frac{TRpICp}{k_{aRIC}}$$

$$a_1 = -\frac{T^2 A + 2T(RRpCpCe + ICe) + 3IRpCpCe}{k_{aRIC}}$$

with $A = (RCe + RpCe + RpCp)$

$$a_2 = -\frac{T(RRpCpCe + ICe) + 3IRpCpCe}{k_{aRIC}}$$

$$a_3 = -\frac{IRpCpCe}{k_{aRIC}}$$

where

$$k_{aRIC} = T^3 + T^2 A + T(RRpCpCe + ICe) + IRpCpCe$$

The single parameter estimates are then calculated from the coefficients found. Since in the simulations the model parameters are known, the relative errors of the estimations can be calculated. Due to the big numerical differences between expected values (R= 2.3 to 5 mbar/l/s, C= 25 to 75 ml/mbar; I= 0.01 mbar/l/s^2; Rp= 900 mbar/l/s; Ce= 0.3 ml/mbar) a scoring system was used to give 2, 1 or 0 points to the error levels <5%, 5-20% and >20% for R, C and Rp, and <100%, 100-200% and >200% for I and Ce. To summarize all simulated cases of a single model, the scores were averaged and total scores in percentage express the quality of the estimation. Because outliers may appear, the variable *Pfound* indicates the percentage of cycles whose estimations for the basic parameters lay inside the established physiological range defined as R: 1 to 30 mbar/l/s and C: 10 to 300ml/mbar.

Using the identified transfer function, a known flow is given to the system to get a reconstruction of the output signal representing the driving pressure P*drive*. Subtracting Paw from P*drive* returns the reconstruction of Pdi. Double cross-validation was done by using half of the breathing cycles for identification and the other half for reconstruction, and repeating the process after interchanging the halves. The reconstructions are compared to the measured pressures by calculating their inspiratory pressure-time-products (PTPinsp) as the area under the curve during inspiration and the chi-square value (X^2). For overall evaluation of the reconstructions, the amount of successful fits ($X^2 < X_c^2$, $p<0.05$) was calculated.

3 Results

3.1 Computer simulations

Six sets of parameter were simulated with and without noise. Table 1 shows the overall quality (0 to 100% where 100% is the best) of the estimations per model.

Table 1 Percentage of successful reconstructions per model using simulations

	Noise	OE	ARX	ARMAX
RC	-	100	100	100
	x	100	31.3	100
RIC	-	75.0	79.2	70.8
	x	70.8	0.0	12.5
eRC	-	83.3	83.3	83.3
	x	75.0	31.3	75.0
eRIC	-	62.5	65.6	62.5
	x	59.4	0.0	12.5
aRC	-	100	100	100
	x	100	18.8	15.6
aRIC	-	17.5	15.0	12.5
	x	17.5	15.0	12.5

The exactitude of ARX clearly diminishes in the presence of noise. Most errors are found in I, revealing the disad-

vantages of choosing models including it. The estimation of parameters from aRIC was problematic with any identification model. The images 2 and 3 display comparisons of *Pfound* and of the amount of successful fits per model.

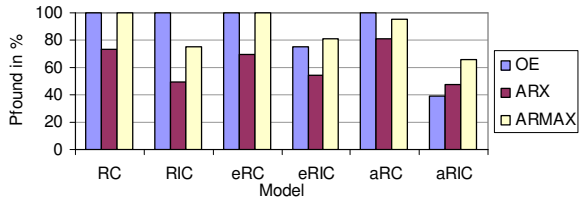

Image 2 *Pfound* per model using simulations

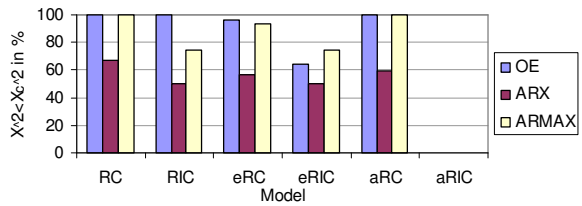

Image 3 Percentage of successful reconstructions per model using simulations

3.2 Lung simulator LS4000

This series of simulations permitted to analyze the models in the presence of real noise and offsets. According to the previous results, the analysis was limited to RC, eRC and aRC. Six sets of parameters were simulated with the lung simulator LS4000 (Dräger, Lübeck). The results show low performance of ARX and are summarized in table 2.

Table 2 *Pfound* and percentage of successful reconstructions of Pdi per model using data from the LS4000

		OE	ARX	ARMAX
Pfound	RC	100.0	65.2	100.0
	eRC	100.0	65.2	100.0
	aRC	98.0	52.9	88.7
$X^2 < X_c^2$	RC	100.0	64.5	99.2
	eRC	100.0	62.7	100.0
	aRC	97.7	21.5	80.6

3.3 Data from volunteers and patients

According to the results from the simulations, OE was selected to analyze models with real data. Table 3 shows the mean values of all model estimates (R, Rp in mbar/l/s; C, Ce in ml/mbar).

The values of R and C are similar between models and lay in the ranges expected for volunteers and patients, but the results for Rp are extreme and lack physiological meaning, indicating over-parameterization. Still, all estimates were used to reconstruct Pdi. The agreement between PTPinsp of measured and reconstructed data was for all models high (R^2= 0.71 to 0.97) and similar (difference in R^2 per subject between models= 0 to 0.1).

Table 3 Estimates for 3 volunteers (V) and 3 patients (P) using RC, eRC and aRC

Subject	Model	R	C	Rp	Ce
V1	RC	4.59	75.21		
	eRC	4.59	75.72	-4.4E+06	
	aRC	5.69	71.74	-2.6E+06	6.79
V2	RC	3.88	93.46		
	eRC	3.89	98.34	-9.2E+05	
	aRC	4.56	99.34	-9.2E+05	13.55
V3	RC	6.01	126.59		
	eRC	6.01	128.01	-2.1E+06	
	aRC	6.55	128.35	-1.9E+06	6.72
P1	RC	10.79	92.72		
	eRC	10.79	95.26	-1.7E+06	
	aRC	10.43	100.63	-4.1E+05	4.45
P2	RC	4.73	95.19		
	eRC	4.73	97.16	-1.8E+06	
	aRC	5.07	101.46	-9.4E+05	5.4
P3	RC	5.87	104.28		
	eRC	5.87	104.83	-3.5E+06	
	aRC	7.18	109.93	-4.5E+06	7.77

Table 4 shows the percentage of estimates inside the physiological range and the percentage of successful reconstructions for the real data.

Table 4 Comparison of models for 3 volunteers (V) and 3 patients (P)

Subject	*Pfound* [%]			$X^2 < X_c^2$ [%]		
	RC	eRC	aRC	RC	eRC	aRC
V1	98.9	98.9	97.7	66.7	78.2	83.7
V2	97.0	97.0	91.0	70.8	43.1	62.3
V3	97.5	97.5	80.2	68.4	82.3	93.8
P1	98.8	98.8	86.3	44.3	68.4	98.6
P2	97.6	97.6	91.8	63.9	74.7	74.4
P3	100	100	95.6	95.6	95.6	97.7
mean	98.3	98.3	90.4	68.3	73.7	85.1

Interestingly, while the mean number of outliers was lower for RC (1.7%) and eRC (1.7%) than for aRC (9.6%), more reconstructions fitted well ($X^2 < X_c^2$, $p<0.05$) to the measured data when using aRC (85.1%) than when using eRC (73.7%) or RC (68.3%). Image 4 shows the measured Pdi from a sample cycle and its reconstructions.

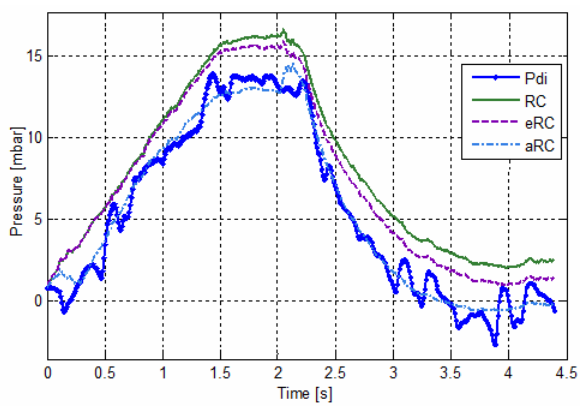

Image 4 Sample reconstructions of real Pdi

4 Conclusions

The computer simulations showed high susceptibility to errors in the identification of the models RIC, eRIC and aRIC containing the inertial parameter I. Noise notably affected the identification by ARX. The identification of aRIC was often problematic due to over-parameterisation. The measurements with the lung simulator showed almost identical results for RC and eRC, and a more exact identification by OE than by ARMAX.

The identification by OE of the models RC, eRC and aRC was successfully implemented to the real data. Increasing complexity of the models directly led to an improvement in the reconstruction of output pressure accompanied by a slightly higher number of outliers. Although it is of course not possible to establish one single model as the best fitting model for all real subjects, the results demonstrate that in several cases the use of the eRC and aRC models may help to improve the quality of the assessment of the respiratory work and thus, to properly set ventilatory support.

5 References

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