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Measuring time-varying respiratory mechanics during anesthesia

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Abstract: We introduce a simple measurement technique which can track sudden and/or transient changes in respiratory mechanics even in unsteady respiration. Respiratory signals are segmented into single-breath signals. Breaths contaminated with noise produced by unsteadiness are discarded manually. A linear single-compartment model is fit to the data of "noise-free" single breaths, estimating its model parameters. Respiratory mechanics is interpreted on the basis of breath-to-breath changes in the parameter estimates. The technique was tested in anesthetized subjects with unstable respiratory conditions. It was shown that the technique was noise insensitive and that the estimated model parameters well reflected the dynamic changes in respiratory mechanics. Although our method provides limited information compared with more sophisticated measurements, it may be useful when respiration is unstable, as frequently seen during light anesthesia or respiratory care.

Key words: Respiratory mechanics, Mathematical model, Unstable respiration, Noise

Introduction

There are two approaches to measure respiratory mechanics. One employs perturbation (excitation) of the respiratory system, e.g., flow interruption [1], relaxed expiration [2], and forced oscillation [3]. It essentially requires a perturbation device and discontinuation of respiration, though it generally provides more in-depth information on the respiratory system than other approaches. It is well-suited for steady-state measurements. The other way to measure respiratory mechanics is to examine the time-domain relationship between flow and pressure wave forms during either spontaneous breathing or mechanical ventilation. Although the latter provides limited information, it allows the tracking of sudden changes in respiratory mechanics with neither an excitation device nor cessation of respiration. Novel techniques have been proposed to monitor sudden or transient changes using the latter approach [4–6]; they are able to follow the changes occurring even within a single breath. They are, however, very sensitive to noise, either intrinsic or extraneous to the system. Under light anesthesia such as the induction or the awakening phases, unstable respiration is often produced by movements, cough, bucking, and swallowing, resulting in noisy respiratory signals. This noise prevents more complex techniques from analyzing suddenly changing respiratory mechanics. We, therefore, introduce a simple technique which can trace sudden and continuous variations in respiratory mechanics even using data contaminated such noise. Our technique is not intended for no-line data analysis.

Methods

The protocol was approved by the Chiba University Ethical Committee and written informed consent was obtained from the adult subject and the guardian of the infant.

Theory

We consider here the respiratory system during mechanical ventilation. Since the respiratory signals are roughly sinusoidal under these conditions, the respiratory system can be approximated to a single-compartment system (see Appendix). We, therefore, employ a linear single-compartment model (Fig. 1). Assuming airway flow ($\dot{V}$) as the input, the output air-

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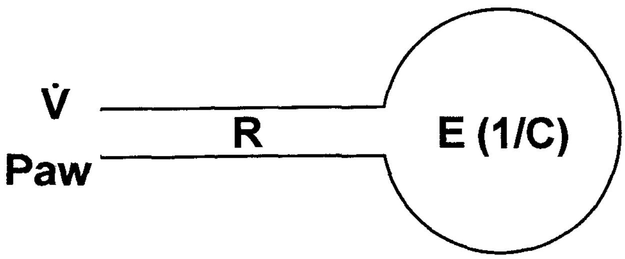


Fig. 1. Schematic representation of a linear single-compartment model. The model consists of a single airway conduit connected in series with an alveolus surrounded by parenchymal tissue. The airway and the alveolar region are represented mechanically by a resistance (R) and an elastance (E) [the inverse of compliance (C)], respectively. *Paw* and $\dot{V}$ denote pressure and flow measured at airway opening, respectively

way pressure (Paw) is defined by the differential equation,

$$\mathrm{Paw} = \mathrm{R}\dot{\mathrm{V}} + \mathrm{EV} + \mathrm{P_0}, \tag{1}$$

where V is ventilation volume (the numerical integration of $\dot{\mathrm{V}}$); R and E are resistance and elastance (the inverse of compliance) of the respiratory system, respectively; $\mathrm{P_0}$ is a term representing the pressure at end-expiration, for example, which is positive when positive-end expiratory pressure (PEEP) is applied. Substituting $\dot{\mathrm{V}}$ and V as the independent variables, and Paw as the dependent variable into Eq. 1, the coefficients R, E, and $\mathrm{P_0}$ are obtained by a x^2 multiple linear least-squares regression analysis which minimizes the cost function,

$$X^2 = \frac{1}{N}\sum_{i=1}^{N}[Paw(i) - \overline{Paw}(i)]^2, \tag{2}$$

where N denotes the number of data points. Paw and $\overline{Paw}$ denote measured and estimated Paws, respectively.

Measured respiratory signals are segmented into single-breath data (Fig. 2). First, end-expiratory points (defined as bottoms, local minima) of the volume signal are determined by a bottom-detection algorithm. One breath is defined as the period from a local minimum to the subsequent local minimum of the volume signal. Based on this definition, all the respiratory signals are segmented into single-breath signals. Following breath-by-breath segmentation, breaths whose signals are contaminated by noise are discarded manually for further analysis. Noise here includes the effects of cough, movement, esophageal spasm (involuntary contraction of esophageal muscle), as well as bucking and swallowing (Fig. 3a,b).

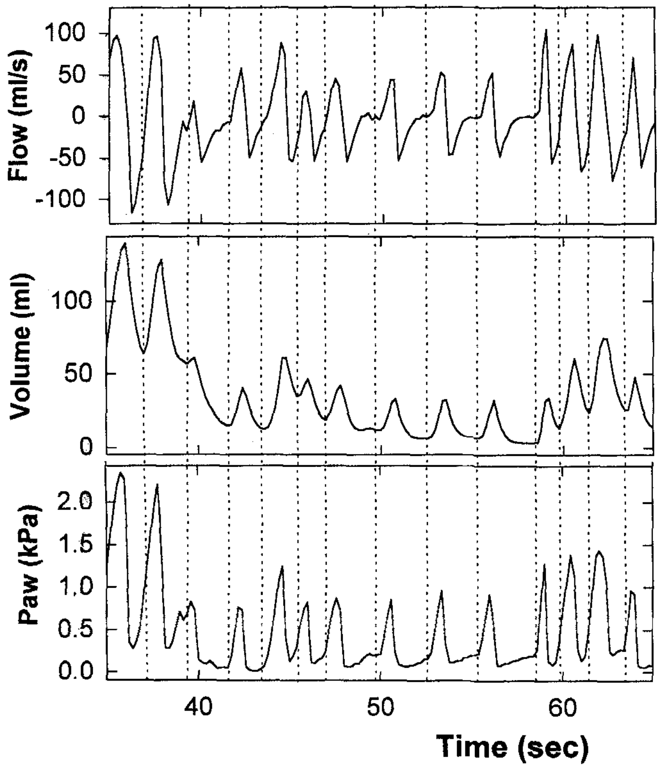
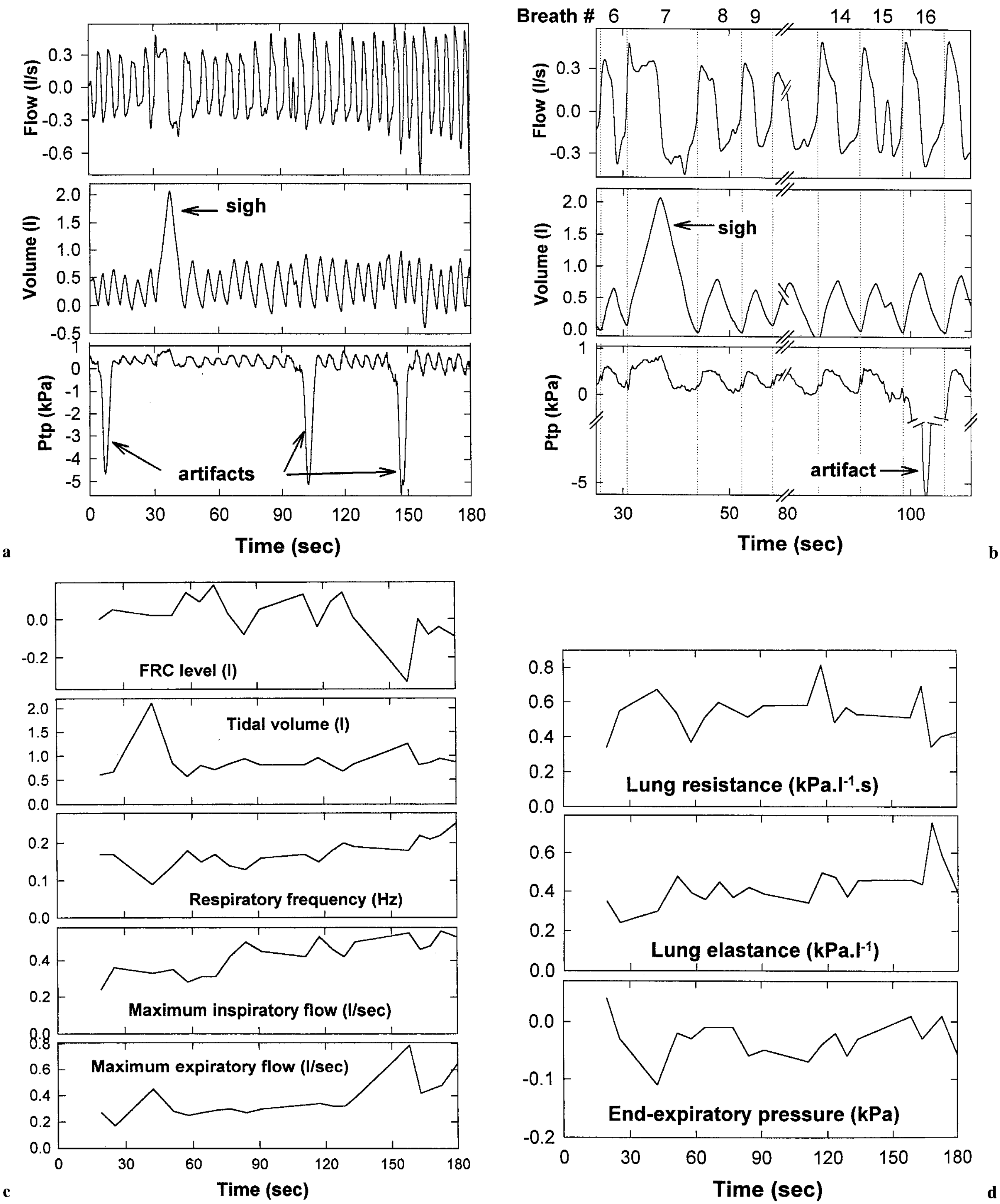


Fig. 2. Breath-by-breath segmentation of respiratory signals measured during mechanical ventilation in an infant. Airway flow (*Flow*), ventilation volume which is the numerical integration of airway flow (*Volume*), and airway pressure (*Paw*) are shown. Each individual breath is segmented with *ertical dashed lines*

Fig. 3. a Example of respiratory signals in a spontaneously breathing subject during N_2O-O_2 anesthesia. Airway flow (*Flow*), ventilation volume (*Volume*), and transpulmonary pressure (*Ptp*) signals are presented. Transpulmonary pressure was obtained by subtracting esophageal from mouth pressures. A *sigh* is recognized in all the signals at approximately 35 s. Large downward deflections, indicated *artifacts* with *arrows*, are seen only in the Ptp signal. They were seemingly produced by involuntary contraction of the esophageal muscle. They could mislead results of the parameter estimation. **b** A part of Fig. 3a is enlarged. Each breath is isolated by the breath-by-breath segmentation program as indicated with *dotted ertical lines*. The Ptp signal of the 16th breath is contaminated by noise. Therefore, the 16th breath is discarded from further analysis. **c** Breath-to-breath changes in respiratory conditional parameters. The end-expiratory level of lung volume (*FRC le el*), tidal volume, respiratory frequency, and maximum inspiratory and expiratory flows are calculated from the single-breath data. They are plotted on a time axis. **d** Breath-to-breath changes in lung mechanical parameters are presented; lung resistance and elastance, and end-expiratory pressure on *top, middle*, and *bottom panels*, respectively



Flow (l/s)
Volume (l)
sigh
Ptp (kPa)
artifacts
Time (sec)
a
Breath # 6 7 8 9 14 15 16
Flow (l/s)
Volume (l)
sigh
Ptp (kPa)
artifact
Time (sec)
b
FRC level (l)
Tidal volume (l)
Respiratory frequency (Hz)
Maximum inspiratory flow (l/sec)
Maximum expiratory flow (l/sec)
Time (sec)
c
Lung resistance (kPa.l⁻¹.s)
Lung elastance (kPa.l⁻¹)
End-expiratory pressure (kPa)
Time (sec)
d

Parameter estimation with the single-compartment model described above is performed with the "noise-free" single-breath data from breath to breath. The estimated respiratory mechanical parameters, R and E, of the individual breaths are plotted on a time scale.

Experiments

We measured airway flow ($\dot{V}$) and pressure (Paw) at airway opening in an infant anesthetized, intubated, and paralyzed with N_2O-O_2-sevoflurane and vecuronium. Both tidal volume and ventilatory frequency were intentionally varied continuously with a wide distribution using manual artificial ventilation. The changes in respiratory system resistance and elastance were computed using Eqs. 1 and 2.

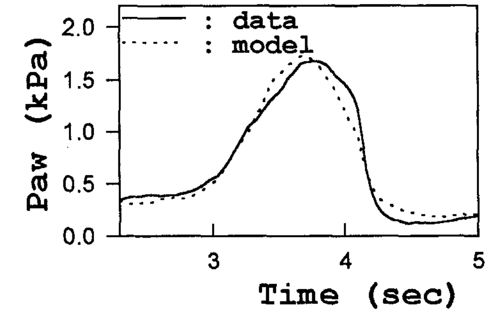
Respiratory signals were also measured in a subject anesthetized with O_2-N_2O during spontaneous breathing via a face mask. We measured mouth pressure (Pm) and $\dot{V}$ at the face mask, and esophageal pressure (Pes) by an esophageal balloon method. Transpulmonary pressure (Ptp) was calculated as the difference between Pm and Pes. We computed the changes in lung resistance and elastance, substituting Ptp for Paw in the left side of Eq. 1.

Using the single-breath data, we computed breath-to-breath changes in respiratory conditional parameters which likely affect respiratory mechanics, i.e., end-expiratory lung volume (functional recidual capacity, FRC level), tidal volume, respiratory frequency, and maximum inspiratory and expiratory flows.

Results

Figure 2 shows the breath-by-breath segmentation employed in our technique. Figure 4 shows an example of the computer output of the parameter estimation applied to single-breath data. As presented in the inset figure, fitting is fairly good, suggesting that the model employed is acceptable. Figure 3 shows the measured respiratory signals, and breath-to-breath changes in respiratory conditional and lung mechanical parameters in a spontaneously breathing subject. As presented in Fig. 3a,b, it is relatively easy to identify contamination by noise which can mislead the parameter estimation. Breaths which are contaminated by noise are discarded manually for further analysis. Figure 3c demonstrates the serial changes in respiratory conditional parameters obtained in association with the breath-to-breath parameter estimation. Figure 3d plots the changes in lung mechanical parameters. Figure 5 demonstrates the measured signals and the changes in respiratory conditional and mechanical parameters in a paralyzed and artificially ventilated infant. Unstable ventilation created intentionally is clear (Fig. 5a), and is reflected in appreciable variations in the conditional parameters shown in Fig. 5b. Figure 5c demonstrates substantial fluctuation in the mechanical parameters which were presumably produced by the unstable ventilation.

Results of #4 breath are



parameter	Estimated SD
R = 8.13 (kPa.l^{-1}·s)	(0.02)
E = 14.2 (kPa.l^{-1})	(0.0)
P_0 = 0.05 (kPa)	(0.00)

x^2 = 6.16e03

full covariance matrix

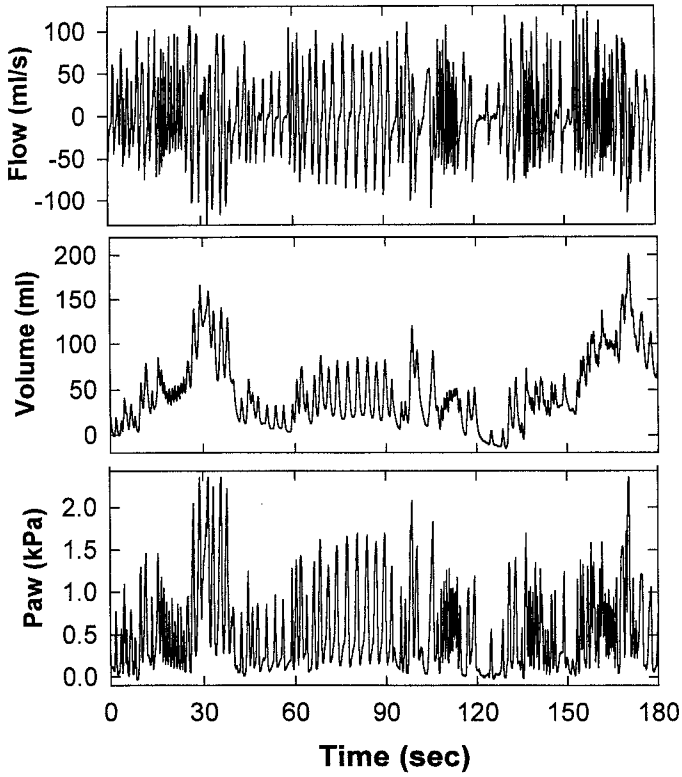
3.97e-10	5.43e-12	-1.56e-10
5.43e-12	2.05e-09	-8.43e-08
-1.56e-10	-8.25e-08	4.33e-06

Fig. 4. A computer output of the model fitting to the data of a single breath. In the *top panel*, *solid* and *dashed lines* indicate the data and the best fit model, respectively. The parameter values, their estimated standard deviations, the value of the cost function, x^2, and the full covariance matrix are tabulated for the best fit model

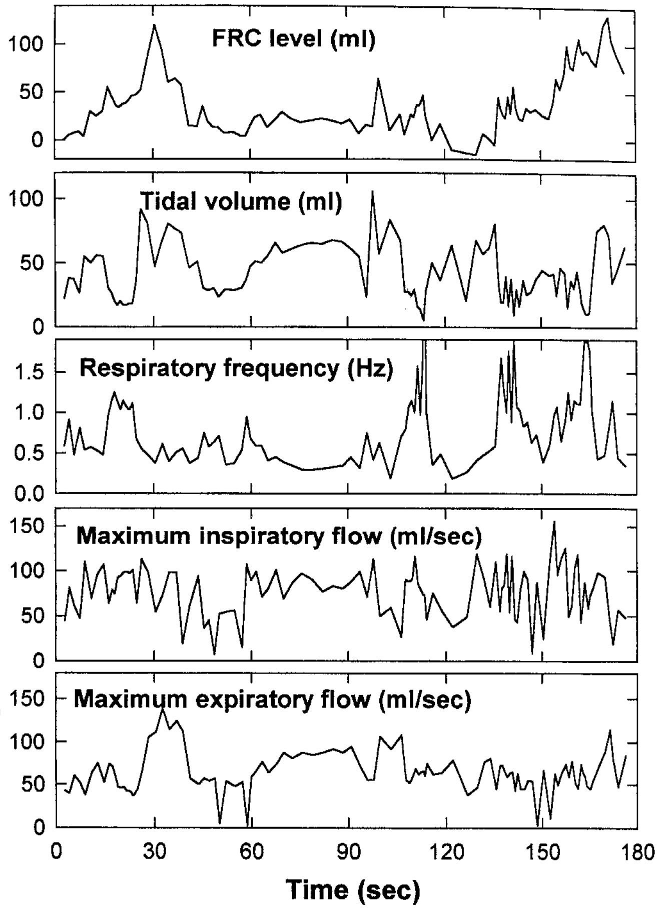
Discussion

We employed breath-by-breath segmentation: (1) to track breath-to-breath changes in respiratory mechanical parameters, and (2) to discard breaths whose signals are contaminated by noise.

From the viewpoint of tracing rapid changes in respiratory mechanics, the recursive least-squares techniques are much better than ours [4–6]. They can be used to track the changes in mechanical parameters occurring even within a single breath. However, they are very sensitive to noise and it is difficult to minimize the influence of noise. Furthermore, it is almost impossible for them to eliminate the effect of biologically intrinsic noise on the computation of respiratory mechanics. Such noise is often produced by movements, cough, bucking, swallowing, and esophageal spasm in



a



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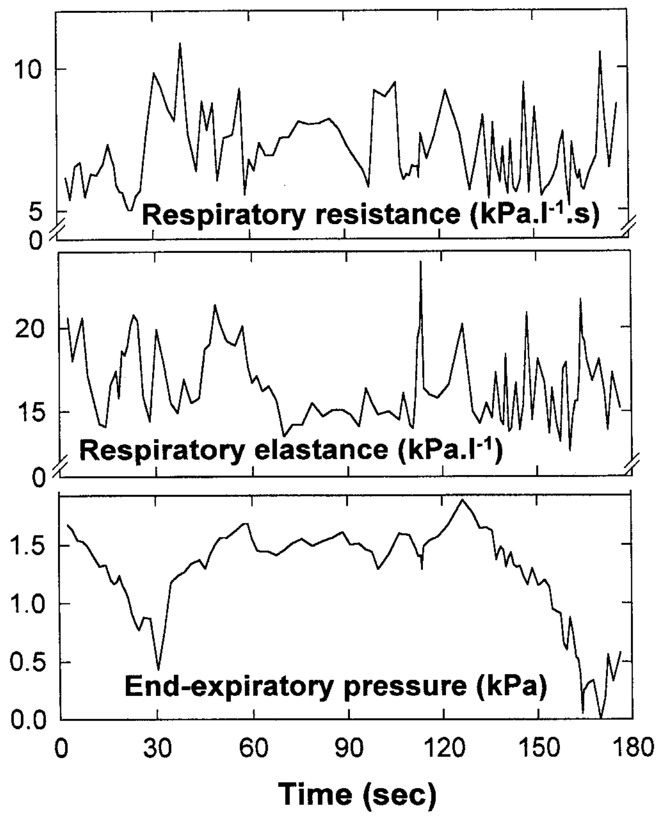

c

Fig. 5. **a** Respiratory signals, **b** breath-to-breath changes, and **c** mechanical parameters in a mechanically ventilated and paralyzed infant during anesthesia. A wide variation of both tidal volume and respiratory frequency were intentionally produced. Its effects on the conditional and the mechanical parameters are clearly observed in **b** and **c**

unstable respiration during light anesthesia or respiratory care.

Dechman et al. [7] employed a block-by-block analysis, with each block containing a multiple breaths, to assess stepwise changes in respiratory mechanics. Their technique is similar to ours, with the only difference being the size of segmentation. The effect of noise on respiratory mechanical computation in their technique is essentially similar to ours. Only the breaths contaminated by noise are required to be discarded in our technique. In their method, by contrast, even if only one breath in a block is contaminated by noises, the whole block should be disregarded to obtain reliable estimates of the respiratory mechanical parameters. In this respect, our breath-by-breath segmentation is more efficient.

There are several measurement techniques of respiratory mechanics which can be carried out in anesthetized patients. Though the flow interruption [1] and the relaxed expiration [2] techniques are relatively simple and provide more information than ours, they require muscle relaxation and discontinuation of respiration. Forced oscillation methods provide a detailed depiction of respiratory mechanics, however the techniques are highly complex [3]. They are, therefore, not advantageous in analyzing rapidly changing respiratory mechanics. On the other hand, our novel technique requires neither paralysis nor cessation of respiration and is based upon single-breath data during either mechanical ventilation or spontaneous breathing. Our method appears well suited for the analysis of time-varying changes in respiratory mechanics during anesthesia, though the mechanical description is expressed by only two parameters which brings with it certain inherent limitations.

The results, as presented in Fig. 2, suggest that the linear single-compartment model is a reasonable representation. Lung or respiratory mechanical structures can be described in more complex models such as two-compartment models [2,8] and nonlinear models [9,10], but respiratory signals during mechanical ventilation or spontaneous breathing do not contain a wide range of frequency components, indicating that the respiratory system behaves as a single-compartment system (see Appendix). Therefore, the single-compartment model is adequate to obtain rough estimates of quantitative changes in respiratory mechanics in a clinical situation.

Respiratory mechanics are known to be influenced by various respiratory conditions such as lung volume, frequency, respiratory flow, and tidal volume [11]. Concomitant changes in those conditional parameters are easily obtained simultaneously with the breath-by-breath model fitting as shown in Figs. 3c and 5b. Examining the correlation between the conditional and the mechanical parameters may allow us to understand in greater detail the changes that occur in respiratory mechanics during unsteady respiratory conditions, such as during induction or awakening periods of anesthesia.

In summary, we developed a technique to measure sudden and/or continuous changes in respiratory mechanics even during unstable respiration. Respiratory signals were segmented into single breaths and noisy breaths were disregarded. Then a linear single-compartment model was fit to each noiseless breath with parameter estimation. Our method was shown to be relatively noise insensitive and the estimated model parameters reflected dynamic changes in respiratory mechanics under unsteady respiration.

Appendix

Two-compartment models for the respiratory system are formulated in general,

$$\dot{P} + K_1 P = K_2 \ddot{V} + K_3 \dot{V} + K_4 V + K_5, \tag{A1}$$

where K_i are constants. P and $\dot{V}$ are pressure and flow, respectively. $\dot{P}$ and $\ddot{V}$ are the time-derivatives of P and $\dot{V}$, respectively, and V is the time-integral of $\dot{V}$. Then Fourier-transforming Eq. A1 and solving it for $P/\dot{V}$, the following equations are obtained,

$$R = (K_2\omega^2 + K_1K_3 - K_4)/(\omega^2 + K_1^{\,2}), \tag{A2}$$

$$E = \left\{(K_3 - K_1K_2)\omega^2 + K_1K_4\right\}/(\omega^2 + K_1^{\,2}), \tag{A3}$$

where ω is angular frequency (2πf: f frequency). R and E denote resistance and elastance of the respiratory system, respectively. Equation A2 indicates the frequency-dependent behavior of R that has been well documented in previous studies [8]. However, when respiratory signals contain only a single frequency, i.e., the signals are purely sinusoidal, Eqs. A2 and A3 indicate that at the frequency R and E are determined uniquely and that the respiratory system behaves as a single-compartment system. In the physiological range of frequency, respiratory signals can be approximated by a sinusoidal [11].

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