Real-Time Estimation of Lung Model Parameters and Breathing Effort During Assisted Ventilation

Thomas Schauer * **Olaf Simanski** **

* *Technische Universität Berlin, Control Systems Group, 10587 Berlin, Germany (e-mail: schauer@control.tu-berlin.de).*
** *Hochschule Wismar - University of Applied Sciences: Technology, Business and Design, Computational Engineering and Automation Group (CEA), 23966 Wismar, Germany (e-mail: olaf.simanski@hs-wismar.de)*

Abstract: The estimation of lung mechanics' parameters and the patient's residual volitional breathing effort is a prerequisite to adjust the parameters of assisted ventilation in a patient-individual manner. A real-time capable approach is investigated that estimates the resistance and compliance of a first-order lung model in conjunction with the intrapleural pressure in real-time. Latter is a measure for the patient's breathing effort. A signal generator model in the form of a Radial Basis Function (RBF) network is assumed for the intrapleural pressure. The Gaussian basis functions are periodic with the breathing cycle duration. This approach does not restrict the signal form of the patient-driven pressure curve. Recursive Least Squares (RLS) with selective forgetting is employed to consider the different dynamics of the estimated model parameters. A time-discrete version of the lung model is used for RLS. Computer simulations reveal that the approach is feasible and that selective forgetting is necessary to obtain satisfactory estimation results.

Keywords: System Identification, Assisted Mechanical Ventilation, Input Estimation, Biomedical Technology, Real-Time Estimation, Simulation Study

1. INTRODUCTION

The individualisation of medical technology has become increasingly important in recent years. On the one hand, the population is getting older and older and still wants to continue living in their own four walls. On the other hand, respiratory diseases are on the rise. Especially in the age of the worldwide COVID-19 pandemic, special attention is being paid to non-invasive ventilation. In (Ashish et al., 2020) it was shown that, where clinically possible, early use of CPAP (continuous positive airway pressure) therapy, including inpatient use, can significantly improve the outcome of patients from respiratory disease. CPAP therapy continues to be used for the treatment of obstructive sleep apnoea syndrome (OSAS). A patient-adapted therapy, and thus a less disruptive therapy, increases the acceptance of this significantly. Russel (2000) as well as Simonds (2006) show how important correctly adjusted parameters are for the treatment of OSAS or in general for assisted non-invasive ventilation. Both for early weaning from ventilation and for the treatment of OSAS it is important to know the individual characteristics of each lung and the proportion of self-breathing correctly. This can be determined by defined tests, such as the high oscillation method, but this is not always goal-directed and possible. Online identification seems more promising. In (Shi et al., 2016) and (Albanese et al., 2013), a simple modelling approach is described, which is explained below. Shi et al. (2016) and Albanese et al. (2013) have presented an online identification approach for the lung parameters R and C using Recursive Least Squares (RLS). In addition, Albanese et al. (2013) and Scheel et al. (2018) estimate the patient's breathing. Albanese et al. (2013) imply the intrapleural pressure in their algorithm, but they assume it to be a slowly changing parameter of the underlying regression model. Their estimates for R and C converge very slowly. Scheel et al. (2018) use a Kalman filter with a sinusoidal signal model. This allows faster estimation but restricts the form of the intrapleural pressure.

The approach described in the contribution goes beyond this, and makes it possible to estimate the proportion of self-breathing independently of the ventilation waveform. A Radial Basis Function (RBF) network with periodic Gaussian functions is used as a signal generator model for the intrapleural pressure. Hence, the signal shape can be arbitrary. This allows a faster estimation of R and C as well as the intrapleural pressure, using the Recursive Least Square (RLS) approach from (Albanese et al., 2013) with selective forgetting to account for the different dynamics of the parameters. Our solution is based on a time-discretised model and requires as inputs the pressure at the entrance of the airway and the lung volume determined by numerical integral of the measured flow. Drifting volume estimation, due to a bias in the flow measurement, and an unknown volume at the beginning of the integration do not pose a problem for the identification approach. The estimation of the patient's own breathing is important for the design of individualised control approaches, as seen in (Scheel et al., 2018), among others.

The paper is organised as follows. Section 2 introduces the lung model and the signal generator model of the breathing effort before the estimation algorithm is described. Afterwards, the results of a computer simulation are reported in Section 3. Finally, Section 4 gives a discussion, conclusions, and an outlook.

2. METHODS

2.1 Lung Model

The following first-order linear model can approximate the breathing mechanics (Albanese et al., 2013; Bates, 2009):

$$p_{\mathrm{aw}}(t) = R_{\mathrm{l}}\dot{V}(t) + \frac{1}{C_{\mathrm{l}}}V(t) + p_{\mathrm{pl}}(t) + p_0 \tag{1}$$

Here, p_{aw} is the airway entry pressure, R_{l} is the airway resistance, C_{l} is the lung compliance and $V(t)$ is lung volume. The lung is surrounded by the pleura. Self-breathing is modelled by the intrapleural pressure source p_{pl}. p_0 is an offset to account for the fact that at the end of exhalation ($\dot{V} \approx 0$ and $p_{\mathrm{pl}} \approx 0$) the respiratory volume $V(t_{\text{end expiration}})$ is equal to the functional residual capacity V_{FRC}:

$$p_0 = -\frac{V_{\mathrm{FRC}}}{C_{\mathrm{l}}} + \underbrace{p_{\mathrm{aw}}(t_{\text{end expiration}})}_{p_{\mathrm{e}}}. \tag{2}$$

Figure 1 shows the electrical analogue of this lung mechanics model.

If only the respiratory flow $\dot{V}$ is measured, the volume difference $\tilde{V}(t) = V(t) - V(0)$ can be determined by numerical integration where $V(0)$ is the unknown lung volume at time instant $t = 0$. This gives

$$p_{\mathrm{aw}}(t) = R_{\mathrm{l}}\dot{\tilde{V}}(t) + \frac{1}{C_{\mathrm{l}}}\tilde{V}(t) + p_{\mathrm{pl}}(t) + p_0 + \frac{1}{C_{\mathrm{l}}}V(0). \tag{3}$$

Hence, the lung dynamics be written as

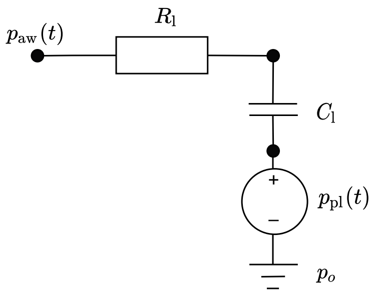

Fig. 1. Electrical analogue of the lung mechanics model.

$$\begin{aligned}\dot{\tilde{V}}(t) = &-\underbrace{\frac{1}{C_{\mathrm{l}}R_{\mathrm{l}}}}_{\alpha}\tilde{V}(t) + \underbrace{\frac{1}{R_{\mathrm{l}}}}_{\beta}(p_{\mathrm{aw}}(t) - p_{\mathrm{e}}) - \underbrace{\frac{1}{R_{\mathrm{l}}}}_{\beta}p_{\mathrm{pl}}(t)\\ &+ \underbrace{\frac{1}{C_{\mathrm{l}}R_{\mathrm{l}}}(V_{\mathrm{FRC}} - V(0))}_{\gamma}.\end{aligned} \tag{4}$$

For the sampling index k and the sampling period Δ one can derive the following discrete-time MISO-ARX model assuming constant input variables p_{aw} and p_{pl} over the sampling interval (Åström and Wittenmark, 1997):

$$\begin{aligned}\tilde{V}(k) = &\underbrace{e^{\alpha\Delta}}_{a}\tilde{V}(k-1) + \underbrace{\frac{\beta}{\alpha}(e^{\alpha\Delta} - 1)}_{b}(p_{\mathrm{aw}}(k-1) - p_{\mathrm{e}})\\ &-bp_{\mathrm{pl}}(k-1) + \underbrace{b\gamma}_{d} + \zeta(k)\end{aligned} \tag{5}$$

The input p_{pl} is assumed to be unknown and will be estimated later together with the offset d and coefficients a and b. The offset term takes into account slow changes in V_{FRC} and integrator drift due to offset errors in the flow measurement. ζ represents measurement noise.

2.2 Signal Generator Model for Intrapleural Pressure

A parameterised signal generator model for the pressure of the pleura is assumed in the form of a Radial Basis Function (RBF) network:

$$p_{\mathrm{pl}}(k-1, \boldsymbol{\kappa}) = \boldsymbol{\kappa}^T \boldsymbol{w}(k) \tag{6}$$

The parameters of the model are contained in the vector $\boldsymbol{\kappa} \in \mathbb{R}^n$. The vector $\boldsymbol{w} \in \mathbb{R}^n$ contains the values of n basis functions, which have as an argument the sampling index k. The basis functions are Gaussian functions with the variance σ and the mean values $\mu_i + l(T_{\mathrm{i}} + T_{\mathrm{e}})$:

$$w_i(k) = \mathrm{e}^{-\frac{1}{2}\left(\frac{\Delta k - l(T_{\mathrm{I}} + T_{\mathrm{E}}) - \mu_i}{\sigma}\right)^2}, \; i = 1, \ldots, n. \tag{7}$$

The integer

$$l = \mathrm{floor}(\Delta k / (T_{\mathrm{i}} + T_{\mathrm{e}})) \tag{8}$$

yields a periodicity of the basis functions with the respiration cycle, which is assumed to be constant. Here T_{i} is the inspiration duration and T_{e} is the expiration duration. The time $k = 0$ coincides with the beginning of an inspiration phase. The μ_i are chosen as

$$\mu_i = \frac{(i-1)T_{\mathrm{i}}}{(n-1)}, \; i = 1, \ldots, n. \tag{9}$$

2.3 Assisted Ventilation

In the case of controlled positive pressure ventilation, the pressure $p_{\mathrm{i}} > 0$ is applied during the inspiration phase. During the expiration phase, a small positive pressure p_{e} (PEEP - Positive End-Expiratory Pressure) is maintained

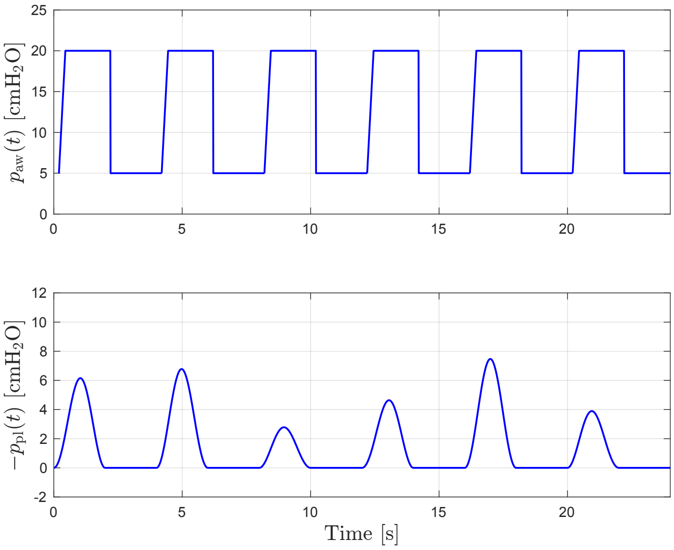

Fig. 2. Pressure curves over six breathing cycles.

to keep the airways open. Ventilation is supportive to the patient's weak spontaneous breathing and is triggered by a flow increase.

2.4 Real-Time Estimation

For simultaneously estimating the parameters of the lung and pleural pressure generator model, the discrete-time ARX model (5) can be expressed as a linear regression model

$$\underbrace{\tilde{V}(k)}_{y(k)} = \underbrace{(a\ b\ b\kappa_1\ \dots\ b\kappa_n\ d)}_{\boldsymbol{\Theta}^T} \underbrace{\begin{pmatrix} \tilde{V}(k-1) \\ p_{\mathrm{aw}}(k-1) - p_{\mathrm{e}} \\ -w_1(k) \\ \vdots \\ -w_n(k) \\ 1 \end{pmatrix}}_{\boldsymbol{\varphi}(k)} + \zeta(k) \qquad (10)$$

with a, b and d defined in (5). Here, $y(k)$, $\boldsymbol{\Theta}$, $\boldsymbol{\varphi}(k)$ and $\zeta(k)$ are the measured output, the parameter vector, the regression vector and the measurement noise, respectively. Real-time estimation of the parameters and thus intrapleural pressure can be established by applying the recursive least squares method. Forgetting will be used to take into account the time-variant system behaviour. In order to assign an individual forgetting factor to each parameter according to its dynamics, the following modified RLS procedure with selective forgetting can be applied (Albanese et al., 2013; Saelid and Foss, 1983):

$$\boldsymbol{L}(k) = \frac{\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)}{1 + \boldsymbol{\varphi}^T(k)\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)}$$

$$\hat{\boldsymbol{\Theta}}(k) = \hat{\boldsymbol{\Theta}}(k-1) + \boldsymbol{L}(k)\left[y(k) - \boldsymbol{\varphi}^T(k)\hat{\boldsymbol{\Theta}}(k-1)\right]$$

$$\boldsymbol{P}(k) = \boldsymbol{\Lambda}^{-1}\left[\boldsymbol{P}(k-1) - \boldsymbol{L}(k)\boldsymbol{\varphi}^T(k)\boldsymbol{P}(k-1)\right]\boldsymbol{\Lambda}^{-1}$$

Here $\boldsymbol{\Lambda} \in \mathbb{R}^{(n+3)\times(n+3)}$ is the diagonal matrix with the vector

$$[\sqrt{\lambda_{\mathrm{RC}}}\ \sqrt{\lambda_{\mathrm{RC}}}\ \sqrt{\lambda_{\mathrm{pl}}}\mathbf{1}_{1\times n}\ \sqrt{\lambda_{\mathrm{RC}}}] \qquad (11)$$

Table 1. Initial simulation model parameters.

Parameter	Value
R_{l}	15 cmH$_2$O/L/s
C_{l}	0.05 L/cmH$_2$O
p_0	-35 cmH$_2$O
p_{i}	20 cmH$_2$O
p_{e}	5 cmH$_2$O
T_{i}	2 s
T_{e}	2 s
Noise variance of measured flow	0.0001 L^2/s^2

on its diagonal. λ_{RC} defines the forgetting factor for the slowly changing parameters a, b and d (R_{l} and C_{l} can be determined from the first two). The value λ_{pl} is used for all faster changing model parameters related to the intrapleural pressure. All forgetting factors λ_i, $i \in \{\mathrm{RC}, \mathrm{pl}\}$, lie in the range $(0, 1]$ with typical values close to one.

The RLS algorithm will be initialised with estimates obtained from an initial least squares estimation taking $N > (3+n)$ samples into account. The RLS is therefore activated after collecting the first N input/output samples. N should be chosen to cover at least one inspiration phase.

Using the definitions of a, b, α and β (see (4) and (5)), the estimated lung model parameters and the intrapleural pressure are then obtained by

$$\hat{R}_{\mathrm{l}} = \frac{\Delta(\hat{a}-1)}{\hat{b}\ln(\hat{a})} \qquad (12)$$

$$\hat{C}_{\mathrm{l}} = -\frac{\hat{b}}{\hat{a}-1} \qquad (13)$$

$$\hat{\boldsymbol{p}}_{\mathrm{pl}}(k) = \frac{\hat{\boldsymbol{c}}}{\hat{b}}\boldsymbol{w}(k) \qquad (14)$$

The vector $\hat{\boldsymbol{c}} = \hat{b}\hat{\boldsymbol{\kappa}}$ is part of the RLS-estimated parameter vector $\hat{\boldsymbol{\Theta}}$ (cf. (10)).

3. RESULTS

The proposed online estimation has been tested in computer simulations with the postulated simple lung model using MATLAB/SIMULINK 2021A (The Mathworks Inc., USA). Assumed initial model parameters are listed in Table 1. With a PEEP of p_e =5 cmH$_2$O, the resulting functional residual capacity is V_{FRC}=2 L. The compliance changes with a ramp from 0.05 to 0.06 L/cmH$_2$O from 63 to 66 s. The resistance changes after 25 s from 15 to 10 cmH$_2$O/L/s.

Fig. 2 shows the curves for p_{aw} and p_{pl} that are used in the simulation over the first six breathing cycles. Ventilation always starts 200 ms after detected spontaneous breathing. Self-breathing effort is sinusoidal in the inspiratory phase (maximum value P_{pl}=–10 cmH$_2$O) and is modulated (multiplied) over time with a sinusoidal waveform (0.25-0.75, frequency 0.075 Hz) to simulate changes.

$$p_{\mathrm{pl}}(t) = P_{\mathrm{pl}}\,\mathrm{sat}_0^1\left(\sin\left(\frac{2\pi t}{T_i} - \pi\frac{2}{3}\right)\right)\left(\sin\left(\frac{2\pi 3}{40}t\right)\frac{1}{4} + \frac{1}{2}\right)$$

Please note, that this equation is only valid for the assumed case $T_i = T_e$.

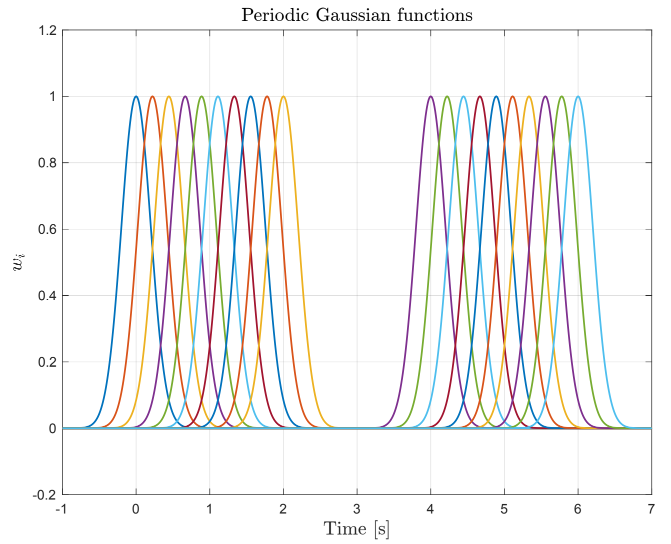

Fig. 3. Periodic Gaussian functions inside the signal generator model for the intrapleural pressure ($n = 10$, $\sigma = 0.2$ s, $T_\mathrm{i} = T_\mathrm{e} = 2$ s).

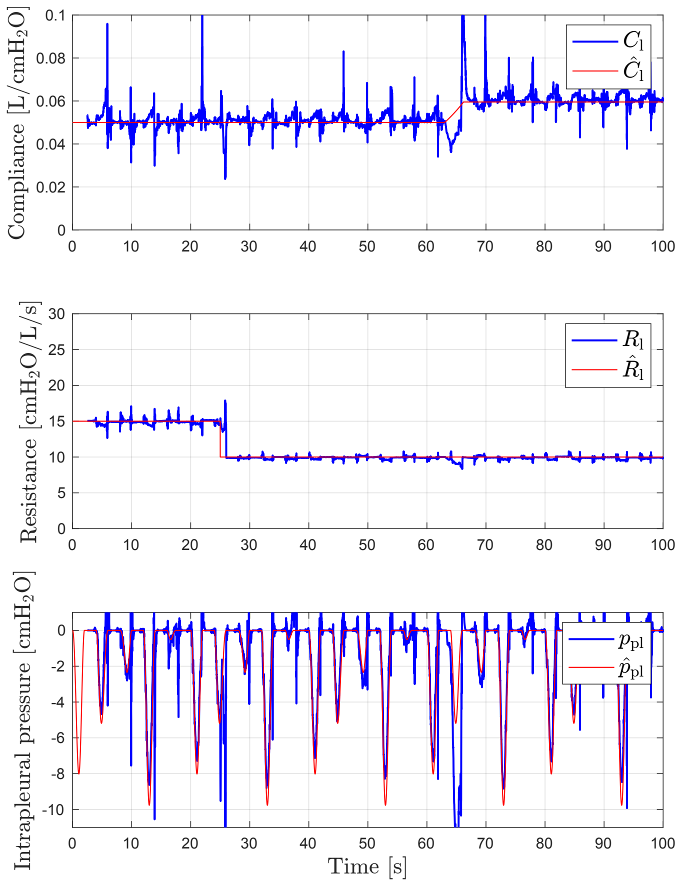

Fig. 4. Identification results ($\lambda_\mathrm{RC} = 0.97$, $\lambda_\mathrm{pl} = 0.97$).

The applied parameters of the RLS with selective forgetting are shown in Table 2. Fig. 3 shows the resulting Gaussian basis functions $w_i, i = 1, \ldots, n$, over two breathing cycles. The inspiration and expiration phases are two seconds each.

The Figures 4 and 5 show the simulation results obtained with the same forgetting factor for all parameters. In both

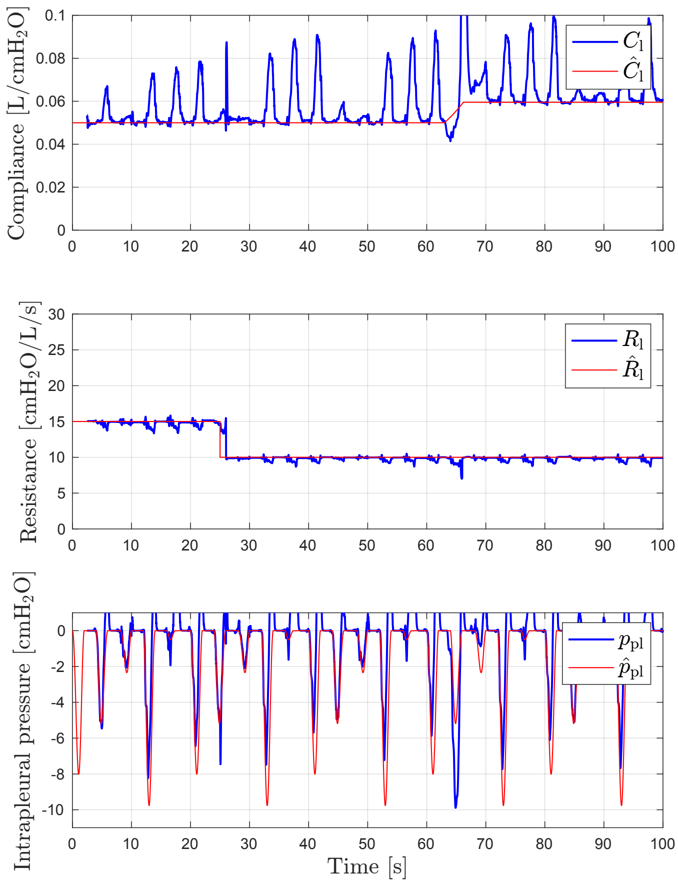

Fig. 5. Identification results ($\lambda_\mathrm{RC} = 0.985$, $\lambda_\mathrm{pl} = 0.985$).

Table 2. RLS settings. Three different settings of λ_pl and λ_RC are simulated.

Parameters	Value		
Δ		0.01 s	
n		10	
σ		0.2 s	
N		250	
λ_pl	0.97	0.985	0.97
λ_RC	0.97	0.985	0.985

cases no satisfactory estimation can be obtained. With $\lambda_\mathrm{pl} = \lambda_\mathrm{RC} = 0.97$ the forgetting factor is too small and all estimates contain undesired high frequent signal components. A reduced forgetting with $\lambda_\mathrm{pl} = \lambda_\mathrm{RC} = 0.985$ improves the result for $\hat{R}_\mathrm{l}$ slightly, but $\hat{C}_\mathrm{l}$ and $\hat{p}_\mathrm{pl}$ still show unsatisfactory results. Further reduction of the forgetting (increase of $\lambda_\mathrm{pl} = \lambda_\mathrm{RC}$) yields less fluctuations in $\hat{C}_\mathrm{l}$ and $\hat{R}_\mathrm{l}$ but offset errors while the higher frequent dynamics of the intrapleural pressure cannot be captured.

By choosing less forgetting for parameters linked with C_l and R_l and more forgetting for parameters linked with $\hat{p}_\mathrm{pl}$, the results shown in Fig. 6 can be obtained. Changes in C_l, $\hat{R}_\mathrm{l}$ and $\hat{p}_\mathrm{pl}$ over time can be successfully tracked in real-time.

Fig. 7 shows the estimate $\hat{p}_\mathrm{pl}$ for the different forgetting settings in a selected time window.

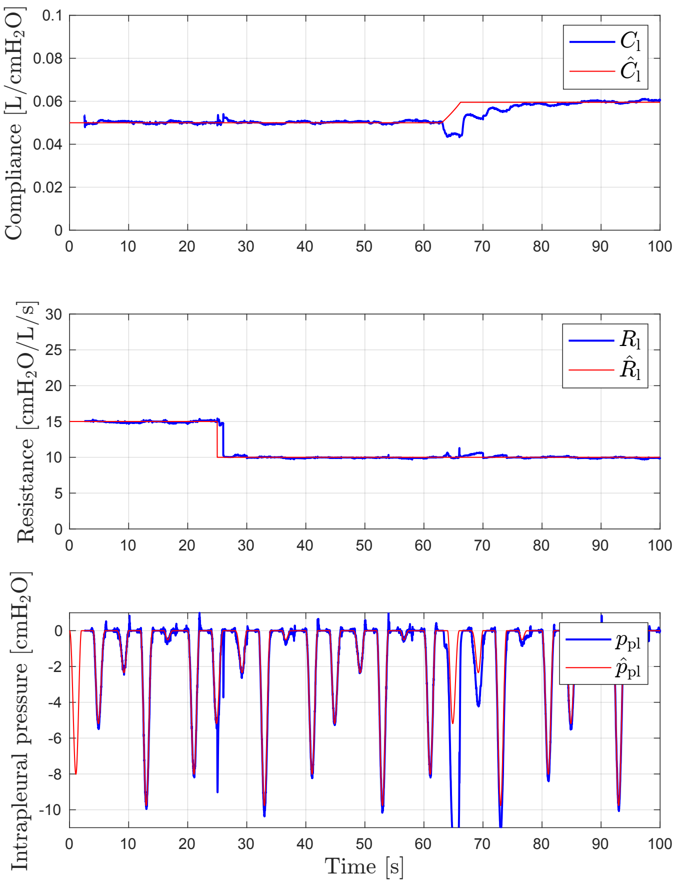

Fig. 6. Identification results ($\lambda_{\mathrm{RC}} = 0.985$, $\lambda_{\mathrm{pl}} = 0.97$).

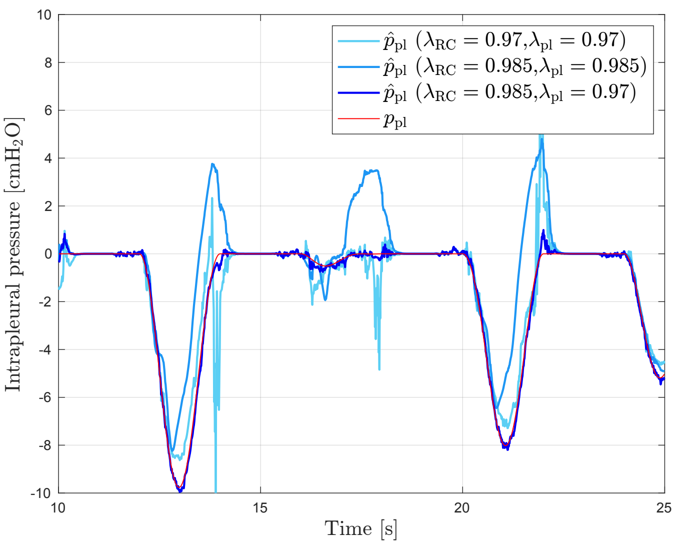

Fig. 7. Estimates of the intrapleural pressure.

4. DISCUSSION AND CONCLUSIONS

The proposed approach is computationally simple. It allows the real-time estimation of lung parameters and the intrapleural pressure from pressure and integrated airflow measurements only. The proposed method is robust for changes of the functional residual capacity V_{FRC} and slow drift of the lung volume caused by bias-affected flow measurements. The usage of a radial basis function network with periodic Gaussian functions to estimate voluntary respiration is a major innovation of this approach. It is assumed that the related pressure curve p_{pl} is periodic, and that expiration is purely passive. The signal form within a period can be arbitrary and can change slowly from breathing cycle to breathing cycle. An implementation of the algorithm on embedded systems is straightforward due to the approach's simplicity. The feasibility of the approach has been demonstrated in computer simulations. It could be shown that selective forgetting needs to be employed to achieve satisfactory estimation results.

Limitations are the simplified lung model and the assumption of a fixed inspiration and expiration period. A continuous adaptation of the periodic Gaussian basis functions for slowly changing breathing cycle duration can be implemented. Future work should validate the approach with a complex lung simulator (TestChest, ORGANIS/AQAI, Switzerland/Germany) before applying the method on experimental data or in closed-loop systems with patients.

The approach can also be used as a biomedical example for RLS with selective forgetting inside university courses on system identification as its complexity is well manageable for students.

REFERENCES

Albanese, A., Karamolegkos, N., Haider, S.W., Seiver, A., and Chbat, N.W. (2013). Real-time noninvasive estimation of intrapleural pressure in mechanically ventilated patients: A feasibility study. In *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. doi: 10.1109/embc.2013.6610723.

Ashish, A., Unsworth, A., Martindale, J., Sundar, R., Kavuri, K., Sedda, L., and Farrier, M. (2020). CPAP management of COVID-19 respiratory failure: A first quantitative analysis from an inpatient service evaluation. *BMJ Open Respiratory Research*, 7(1). doi: 10.1136/bmjresp-2020-000692.

Bates, J.H.T. (2009). *Lung Mechanics: An Inverse Modeling Approach*. Cambridge University Press. doi: 10.1017/CBO9780511627156.

Åström, K.J. and Wittenmark, B. (1997). *Computer-Controlled Systems (3rd Ed.)*. Prentice-Hall, Inc., USA.

Russel, W. (2000). The comfort of breathing: A study with volunteers assessing the influence of various modes of assisted ventilation. *Thorax*, 28(11), 3645–3648.

Saelid, S. and Foss, B. (1983). Adaptive controllers with a vector variable forgetting factor. In *22nd IEEE Conference on Decision and Control*, 1488–1494. doi: 10.1109/CDC.1983.269785.

Scheel, M., Berndt, B., and Simanski, O. (2018). Application of Kalman filter for breathing effort reconstruction for OSAS patients in breathing therapy. *at- Automatisierungstechnik*, 66(12), 1064–1071. doi:10.1515/auto-2018-0067.

Shi, Y., Niu, J., Cao, Z., Cai, M., Zhu, J., and Xu, W. (2016). Online Estimation Method for Respiratory Parameters Based on a Pneumatic Model. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 13(5), 939–946.

Simonds, A. (2006). Risk management of the home ventilator dependent patient. *Thorax*, 61(5), 369–371. doi:10.1136/thx.2005.055566.