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LUNG MODEL PARAMETER ESTIMATION BY UNSCENTED KALMAN FILTER

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Abstract— **Dynamic nonlinear models are the best choice to analyze respiratory systems and to describe system mechanics. In this work, Unscented Kalman Filtering (UKF) was used to estimate the dynamic nonlinear model parameters of the lung model by using the measured airway flow, mask pressure and integrated lung volume. Artificially generated data and the data from Chronic Obstructive Pulmonary Diseased (COPD) patients were analyzed by the proposed model and the proposed UKF algorithm. Simulation results for both cases demonstrated that UKF is a promising estimation method for the respiratory system analysis.**

I. INTRODUCTION

Lung models (more generally respiratory system models) are of great importance in determining respiratory mechanics, especially in patients requiring ventilatory assist. Many respiratory system models were constructed to simulate the interaction between respiratory parameters such as respiratory resistance and airway flow and respiratory compliance and lung volume indirectly [1], [2], [3]. These models were then used to estimate the parameters by applying several methodological approaches [4], [5].

Forced oscillation technique (FOT) [4] and impulse oscillometry (IOS) [6] are the recent favorite techniques and used both in the literature and clinically for the noninvasive respiratory system analysis. These techniques are based on the description of respiratory system mechanics by linear equivalent electrical models of different complexity with lumped parameters. Although applicability and signal processing techniques of the FOT and IOS are still being investigated, the need of the additional hardware and linear and deterministic model approach to the respiratory system force the investigators to go for the more dynamic, nonlinear and stochastic models.

Model of the respiratory system should incorporate the dynamic nature of the respiration. However, dynamic model of the respiratory system should not only track all rapid changes in the parameters but also consider the time-varying nature of the model parameters. Thus appropriate model of the respiration system should be composed of the non-constant terms.

The nonlinear model needs are presented in detail in [1], [2]. The most importance of the nonlinear models is that they reflect the real system related to the gas dynamics inside the airways and structural complexity of the lung and chest wall tissue.

Measured airway flow, mask pressure are only data that can be acquired nonivasively. Random nature of these discrete signals necessitates stochastic signal processing techniques.

In this work, Unscented Kalman Filtering (UKF) [7] was used to estimate the nonlinear model parameters of the lung model by using the measured airway flow, mask pressure and integrated lung volume. In the first simulation, artificially generated airway flow and mask pressure were used for the estimation, then, in the second simulation to validate the model the data from Chronic Obstructive Pulmonary Diseased (COPD) patients were analyzed by proposed model and UKF algorithm.

A. *UKF Background*

The Kalman Filter is an optimal filter for estimating linear model parameters. However, for nonlinear systems Extended Kalman Filter (EKF) [8] was developed. In EKF, the state distribution is approximated by a Gaussian Random Variable (GRV) and nonlinearities were linearized by first-order approximations. However, this introduces large errors in the mean and covariance of the transformed GRV. UKF was developed to address these problems by using deterministically selected sigma points to approximate the state distribution as a GRV. The detailed comparison between EKF and UKF and explanation on the UKF algorithms can be found in [9].

UKF algorithm can be used for both state or parameter estimation or joint/dual estimation. For the general discrete-time nonlinear system state-observation equations are given as:

$$x_{k+1} = \mathrm{F}\left(x_k, w_k, u_k\right) + q_k \tag{1}$$

$$y_k = \mathrm{H}\left(x_k, w_k, u_k\right) + r_k \tag{2}$$

where x_k represents the unobserved state of the system, w_k is the parameter vector, u_k is the known input and y_k is the observed measurement signal. In this work the process noise $q_k \sim N\left(0, Q_k\right)$ and the observation noise $r_k \sim N\left(0, R_k\right)$ are assumed to be additive Gaussian noises.

For the parameter estimation, the parameters are usually considered as a markov process having a state representation of:

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$$w_{k+1} = w_k + n_k \tag{3}$$

where process noise $n_k \sim N(0, N_k)$ is additive Gaussian noise.

The covariance of the process noise in the parameter state representation N_k affects the convergence rate and tracking performance [9]. Although there are several methods to manipulate N_k, in this work N_k is set to fixed diagonal value. Details of the implemented UKF algorithm can be found in [9].

II. LUNG MODEL

In this work one compartment nonlinear lumped parameter electrical model of the lung was used (Fig.1). One compartment model composed of one resistance and one capacitor was adopted because of its simplicity. If basic circuit theory rules are applied to the electric circuit in Fig.1, measured mask pressure $P_{aw}(t)$ equation can be given as:

$$P_{aw}(t) = P_r(t) + P_c(t) - P_{mus}(t) + P_{ven}(t) \tag{4}$$

In the model, R represents the upper airway resistance as the biggest contribution to the resistive pressure lost in the tidal breathing range comes from the upper airways. Rohrer's equation is used to compose the relation between airway flow $\dot{V}(t)$ and mask pressure $P_{aw}(t)$. Thus resistive pressure lost in the model can be given as:

$$P_r(t) = \left(A_u + K_u \left|\dot{V}(t)\right|\right) \dot{V}(t) \tag{5}$$

Although the linear compliance models have been shown to successfully simulate lung tissue behavior for small volume excursions, to generalize the model, dynamic pressure across the nonlinear compliance C was adopted from the [2]. In [2], nonlinear dynamic pressure dependence upon lung volume was given according to the formula:

$$P_c(t) = A_l e^{K_l V(t)} + B_l \tag{6}$$

In (5) and (6), A_u, K_u, A_l, K_l and B_l constitute the unknown parameter vector.

Since the pressure developed in the respiratory system and measured in the patient's mask expend relatively small part of the patient's effort during breathing and big part of the ventilator generated pressure, a series of the independent pressure sources are added to the model. $P_{mus}(t)$ represents the pressure effects on the measured $P_{aw}(t)$ done by the patient's inspiration muscles. Ventilator generated pressure $P_{ven}(t)$ has a direct effect on the $P_{aw}(t)$ as it is the major positive component shaping the waveform. It should be emphasized that pressure sources $P_{mus}(t)$ and $P_{ven}(t)$ are added to the model and reflect only the related effects on the $P_{aw}(t)$, thus should not be seen as a direct lung model functions.

$P_{mus}(t)$ can be approximated by the second-order polynomial function [10]:

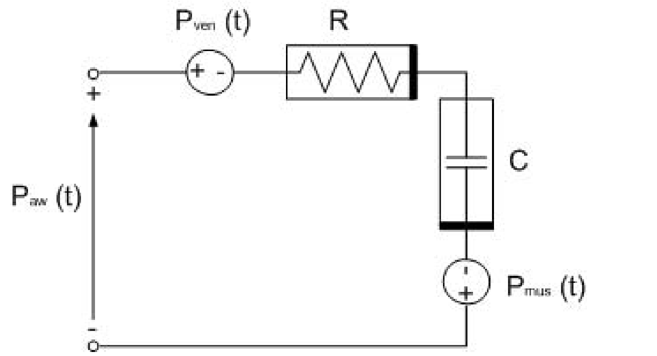

Fig. 1. One compartment nonlinear lumped parameter electrical model of the lung

$$P_{mus}(t) = \begin{cases} -P_{mus\ \max}\left(1 - \frac{t}{T_I}\right)^2 + P_{mus\ \max} & 0 \le t \le T \\ P_{mus\ \max} e^{-t/\tau_m} & T_I \le t \le T \end{cases} \tag{7}$$

where $P_{mus\ \max}$ represents the effect of maximal patient's effort on $P_{aw}(t)$, T_I and T are the inspiration duration time and total duration of one cycle respiration respectively. In this work $P_{mus\ \max}$ is added to the unknown parameter vector whereas T_I and T are set to constant values. Time constant τ_m is important parameter for mostly determining the expiratory asynchrony in the assist ventilation [10]. Constant value was assigned to τ_m in order to mimic the real respiratory system.

Ventilator generated pressure P_{ven} is simulated by the exponential function [10]:

$$P_{ven}(t) = \begin{cases} PEEP & 0 \le t \le t_{trig} \\ P_{ps}\left(1 - e^{-t/\tau_{vi}}\right) & t_{trig} < t \le T_I \\ P_{ps}\left(e^{-t/\tau_{ve}}\right) & T_I < t \le T \end{cases} \tag{8}$$

where P_{ps} represents the maximal ventilation pressure and set to 10 cmH_2O.

Positive End Expiration Pressure (PEEP) was also considered and set to 4 cmH_2O. Ventilator inspiration time constant τ_{vi} corresponds the flow acceleration speed of the ventilator, whereas ventilator expiration time constant τ_{ve} is the ventilator deceleration speed and contributes to the pressure rise at the termination of the inspiration. Both τ_{vi} and τ_{ve} were set to 0.006 s. The inspiration trigger delay of the ventilator t_{trig} was set to 20 ms corresponding to the real world scenario. Above set values for $P_{ven}(t)$ were applied in both simulations.

A. State-Observation Equations of the Lung Model

State variables of the model circuit are the capacitor charge which represents lung volume $V(t)$ and the current through the resistor which represents the airway flow $\dot{V}(t)$. State equations of the lung model are formulated from the model by using Kirchhoff current and voltage laws. First state equation:

$$\frac{dV(t)}{dt} = \dot{V}(t) \tag{9}$$

and from (6)

$$\frac{dP_c\left(t\right)}{dt} = A_l K_l e^{K_l V(t)} \dot{V}\left(t\right) \tag{10}$$

From (4) and (10) second state equation is formulated as:

$$\frac{d\dot{V}\left(t\right)}{dt} = \frac{\dot{P}_{aw}\left(t\right) - \dot{P}_{ven}\left(t\right) + \dot{P}_{mus}\left(t\right) - A_l K_l e^{K_l V(t)} \dot{V}\left(t\right)}{A_v + 2K_v \dot{V}\left(t\right)} \tag{11}$$

Observation equation is the measured mask pressure P_{aw}:

$$P_{aw}\left(t\right) = \left(A_v + K_v \left|\dot{V}\left(t\right)\right|\right) \dot{V}\left(t\right) + A_l e^{K_l V(t)} + B_l - P_{mus} + P_{ven} \tag{12}$$

B. Discretization of the Model Equations for UKF Algorithm

Equations (9), (11) and (12) should be discretized and written in the form of (1) and (2) for UKF algorithm. Thus discrete-time representation of the state-observation equations was derived using the Euler integration method to give the model equations in the matrix form:

$$\begin{bmatrix} V_{k+1} \\ \dot{V}_{k+1} \end{bmatrix} = \begin{bmatrix} \dot{V}_k \\ \frac{P_{aw}^{k+1} - P_{aw}^{k} - P_{ven}^{k+1} + P_{ven}^{k} + P_{mus}^{k+1} - P_{mus}^{k} - A_l^k K_l^k e^{K_l^k V_k} \dot{V}_k}{A_u^k + 2K_u^k \dot{V}_k} \end{bmatrix} + \begin{bmatrix} V_k \\ \dot{V}_k \end{bmatrix} + q_k \tag{13}$$

where k is the discrete time indices and $q_k \sim N\left(0, Q_k\right)$ is the process noise.

Observation equation is represented in discrete form as:

$$P_{aw}^k = \left(A_u^k + K_u^k \left|\dot{V}_k\right|\right) \dot{V}_k + A_l^k e^{K_l^k V_k} + B_l^k - P_{mus}^k + P_{ven}^k + r_k \tag{14}$$

where $r_k \sim N\left(0, R_k\right)$ is the observation noise.

As seen from (13) and (14) the model parameters are written in dynamic form by the time indices k. Thus, parameter state vector is represented as in (3) where $w_k = \left(A_u^k \quad K_u^k \quad A_l^k \quad K_l^k \quad B_l^k \quad P_{mus\ \max}^k \right)^T$.

III. LUNG MODEL PARAMETER ESTIMATION BY UKF

Lung model parameter vector w_k was estimated by using both artificial airway flow and mask pressure signals and the signals recorded from COPD patients. Only the observation equation being nonlinear UKF algorithm was simplified and computational cost was decreased.

Artificial airway flow is simulated as a sinusoidal signal with maximum flow of 0.6 l/s, inspiration time T_I of 1.4 s and total breathing cycle of 3.3 s. Artificial volume is generated by integrating the artificial flow. Artificial $P_{mus}\left(t\right)$ pressure is simulated by using (7). $P_{mus\ \max}$ is set to 1.2 cmH_2O, T_I is 1.4 s and τ_m is 0.8 s. $P_{ven}\left(t\right)$ is generated by (8) with the same constant values as explained in the section II. Finally, $P_{aw}\left(t\right)$ is calculated by. A_u is 0.31 $cmH_2O \cdot l^{-1} \cdot s^{-1}$, A_l is 0.1 cmH_2O, K_u is 0.32 $cmH_2O \cdot l^{-2} \cdot s^{-2}$, K_l is 1.0 and B_l is 0 cmH_2O [2]. Gaussian noise with variance 0.2 is also added to P_{aw} signal as a measurement noise.

TABLE I

UKF ALGORITHM PARAMETERS

Parameter	Simulation I	Simulation II
Initial w_k vector $\hat{w}_0 = \mathrm{E}\left[w_0\right]$	$\hat{w}_0 = [1; 1; 1; 1; 1; 1]$	$\hat{w}_0 = [1; 1; 1; 1; 1; 1]$
Initial w_k covariance matrix $\mathrm{P}_0 = \mathrm{E}\left[\left(w_0 - \hat{w}_0\right)\left(w_0 - \hat{w}_0\right)^T\right]$	$\mathrm{P}_0 = 10^{-1} \cdot \mathrm{I}_{(6,6)}$	$\mathrm{P}_0 = 1 \cdot \mathrm{I}_{(6,6)}$
n_k noise covariance matrix N_k	$N_k = 10^{-5} \cdot \mathrm{I}_{(6,6)}$	$N_k = 10^{-3} \cdot \mathrm{I}_{(6,6)}$
Observation noise variance R_k	$R_k = 0.2$	$R_k = 0.02$
Sigma point scaling parameter α	$\alpha = 0.1$	$\alpha = 0.1$
Higher order scaling parameter β	$\beta = 2$	$\beta = 2$
Scalar tuning parameter κ	$\kappa = 0$	$\kappa = 0$

For the best parameter convergent values, UKF parameters and initial values are set as in Table I. $P_{mus}\left(t\right)$, $P_r\left(t\right)$ and $P_c\left(t\right)$ pressure waveforms are calculated by using convergent values of the model parameters applying (5), (6) and (7) respectively and shown in Fig.2. Fig.3 shows model parameters' convergence waveforms.

In order to verify the applicability of the model, the parameter vector was estimated with the real clinical data. 10 COPD patients were recruited and connected to the non-invasive ventilator (Respironics Inc. BIPAP S/T IPAP is set to 10 cmH_2O and PEEP is set to 4 cmH_2O) via Facemask (Respironics Inc. Spectrum size medium and small). Mask pressure and airway flow were measured by the pneumotachograph and pressure transducer system (Hans Rudolph Inc. Research pneumotachograph system). The sampling rate was 100 Hz.

1 cycle airway flow and corresponding mask pressure was chosen. $P_{ven}\left(t\right)$ is generated by (8) with the same constant values as explained in section II. Table I shows the UKF parameters and initial values for the best parameter convergent. Fig.4 shows $P_{mus}\left(t\right)$, $P_r\left(t\right)$ and $P_c\left(t\right)$ pressure waveforms produced by COPD patient's data.

IV. DISCUSSION

In this work, one compartment nonlinear lung model was constructed and state-observation equations of the model are defined. Model parameters were estimated by UKF estimation method.

Simulation results for both cases demonstrate that UKF well suits to the respiratory system analysis. Moreover, Fig.3 shows the tracking ability of the UKF algorithm. Thus, UKF can be used not only for estimation also for the tracking the parameter changes over some defined time.

In order to evaluate the UKF parameter's effects on the estimation different set of UKF parameter values were tried. Both in the artificial data and in the real measured data $P_{mus\ \max}$ estimation is more robust than the other parameters. The changes of UKF parameter α and process noise covariance N_k had very small effect on the $P_{mus\ \max}$ estimation.

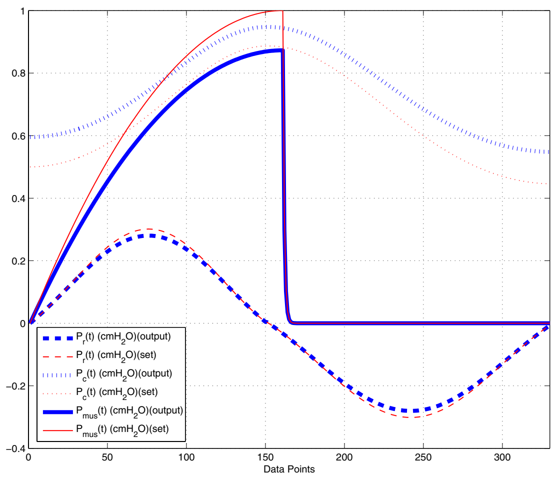

Fig. 2. Typical representation of resistive pressure dissipation curve, capacitive pressure dissipation curve and muscular pressure effects on the airway pressure curve (produced by artificial data)

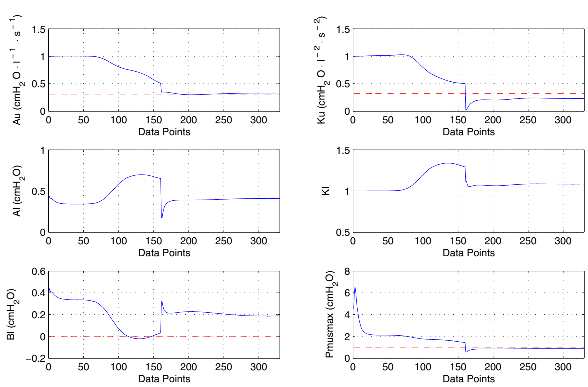

Fig. 3. Typical representation of lung model parameter convergence waveforms (produced by artificial data). The dotted lines represents set values

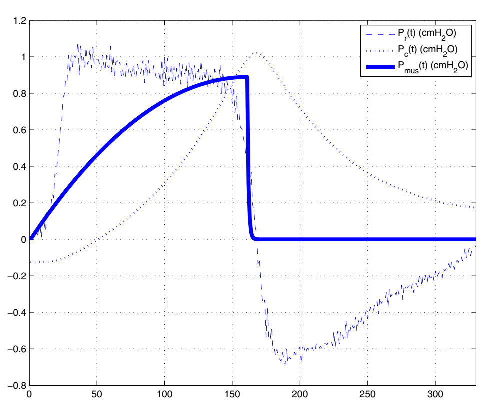

Fig. 4. Typical representation of resistive pressure dissipation curve, capacitive pressure dissipation curve and muscular pressure effects on the airway pressure curve (produced by COPD patient's data)

The most influential UKF parameter on the model parameter estimation were the observation noise variance R_k. Especially for the artificial data when the observation noise variance increased, parameter estimates of UKF got poorer. This observation states that with noisy observed data misleading estimation results could be given.

Convergent effects of process noise covariance N_k were also experienced. In the real data case, the process noise covariance was 100 times higher than it is in the artificial data case. That states that the artificial data is in fact converge more rapidly than the real data.

It is evident from the Fig.2 and Fig.4 that for both measured and produced data the proposed model gives similar results. As it is expected $P_r(t)$ increases right from the onset of the inspiration whereas $P_c(t)$ gradually increases and peaks at the termination of the inspiration. $P_{mus}(t)$ also behaves as an expected manner.

In Fig.4 the effect of trigger time, t_{trig} on the $P_c(t)$ can be seen as a negative part at the onset of the inspiration. This negative part of $P_c(t)$ also results in peak at the $P_r(t)$ curve.

In conclusion, The new method based on UKF was used to estimate the dynamic nonlinear lung model parameters. Resistive and capacitive dissipation pressure curves were presented both for the artificial data and COPD patient's data. In the future work, the developed model should be improved to compose chest wall properties.

V. ACKNOWLEDGMENTS

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REFERENCES

[1] A. G. Polak and J. Mroczka, Nonlinear Model for Mechanical Ventilation of Human Lungs, *Comput. in Biol. and Med.*, vol. 36, 2006, pp 41-58.

[2] A. Athanasiades, F. Ghorbel, J. W. Clark Jr. et al, Energy Analysis of a Nonlinear Model of the Normal Human Lung, *J. Biological Sys.*, vol. 8, 2000, pp 115-139.

[3] T. F. Schuessler, S. B. Gottfried, J. H. T. Bates, A Model of the Spontaneously Breathing Patient: Application to Intrinsic PEEP and Work of Breathing, *J. Appl. Physiol.*, vol. 82, 1997, pp 1694-1703.

[4] R. Farre, R. Peslin, M. Rotger et al, Forced Oscillation Total Respiratory Resistance and Spontaneous Breathing Lung Resistance in COPD Patients, *Eur. Respir. J.*, vol. 14, 1999, pp 172-178.

[5] W. Nikischin, T. Gerhardt, R. Everett et al, A New Method to Analyze Lung Compliance When Pressure-Volume Relationship is Nonlinear, *Am. J. Respir. Care.Med.*, vol. 158, 1998, pp 1052-1060.

[6] J. Hellinckx, M. Cauberghs, K. De Boeck et al, Evaluation of Impulse Oscillation System: Comparison with Forced Oscillation Technique and Body Plethysmography, *Eur. Respir. J.*, vol. 18, 2001, pp 564-570.

[7] S. J. Julier and J. K. Uhlmann, A New Extension of the Kalman Filter to Nonlinear Systems, *in Int. Symp. Aerospace/Defense Sensing, Simul. and Controls*, Orlando, FL, 1997

[8] M. S. Grewal and A. P. Andrews, *Kalman Filtering: Theory and Practice*, Wiley, USA, 2001

[9] E. A. Wan and R. van der Merwe, The Unscented Kalman Filter for Nonlinear Estimation, *in Proc. of IEEE Symposium 2000 (AS-SPCC)*, Alberta, Canada, 2000

[10] Y. Yamada and H. L. Du, Analysis of the Mechanisms of Expiratory Asynchrony in Pressure Support Ventilation: A Mathematical Approach, *J. Appl. Physiol.*, vol. 88, 2000, pp 2143-2150.