ESTIMATION OF THE RESPIRATORY SYSTEM PARAMETERS

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ABSTRACT

In clinical respiratory studies, resistance and the lung compliance are two important respiratory parameters that are often measured by physicians. In this work, Respiratory signals (mask pressure, airway flow, and lung volume) are measured by using artificial lung simulator and mannequin head and respiratory parameters set on the simulator are estimated by the best linear unbiased estimator (BLUE). However, prior to the estimation, muscular pressure signals that symbolize the effect of the respiratory parameters on the respiratory signals are computed by using least mean square (LMS) based adaptive noise canceler (ANC). It is found that LMS filter length considerably effects the filter output and in turn the estimation results. Thus, it is suggested to use misadjustement criterion in LMS-ANC filter to select the filter order by processing the signals that have only one respiratory parameter variation. In conclusion, respiratory parameters are successfully estimated from the muscular pressure signals that are filtered out with appropriate filter lengths.

1. INTRODUCTION

Respiratory system resistance, R and lung compliance, C are the parameters that are widely used for diagnostic purposes by the respiratory physicians. The non-invasive measurement and/or calculation of these parameters is still an unsolved problem.

Frequency analysis of the respiratory system in the form of forced oscillation technique (FOT) have been extensively used for the determination of respiratory parameters [1, 2]. However for the sake of the integrity of the spontaneous breathing with the measurements, time-domain modeling of the respiratory system [3]. In literature [4, 5], it was shown that the respiratory system resistance and lung compliance can be estimated with the parameters of measurable inner mask pressure ($P_{aw}(t)$) by using statistical signal processing methods. In these studies, linear and non-linear respiratory system models with parameters respiratory system resistance and lung compliance were used and these parameters were estimated by using respiratory signals ($P_{aw}(t)$ ve $\dot{V}(t)$) from three different sources. These respiratory signals were obtained by: i) simulation, ii) measurements from healthy subjects or iii) measurements from patients with an accompanying artificial respiratory device. The missing part of these studies which also present a comparison of theoretical estimation methods is that the accuracy of estimation using measured respiratory signals is evaluated in terms of R and C values. This fact requires comparing real R and C values with the estimated R and C values rather than evaluating estimated values and estimator in themselves.

In this study, real respiration signals were produced by artificial lung simulator and mannequin head and then preadjusted R and C parameters were estimated with statistical signal processing methods. Prior to the estimation bye Best Linear Unbiased Estimator (BLUE) [6], the effects of inner mask pressure, airflow rate and lung volume were filtered by using Least Mean Squares (LMS) based Adaptive Noise Canceler (ANC) [7].

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2. RESPIRATORY SYSTEM MODEL

The linear RC respiratory system model represents the basic relationship between the measured respiratory signals ($P_{aw}(t)$, $\dot{V}(t)$) and the respiratory parameters and in general defines the equation of motion of the lung. For the tidal breathing and at the breathing frequency, the discrete form of the model is given by [8]:

$$P_{aw}(n) = \frac{V(n)}{C} + \dot{V}(n)R + P_{mus}(n) \tag{1}$$

where n is the time sample index, $P_{aw}(n)$ is the measured inner mask pressure, $V(n)$ is the lung volume and $P_{mus}(n)$ is the muscle pressure that generates the airflow during respiration. In respiratory system analysis measured $P_{aw}(n)$, $\dot{V}(n)$, $V(n)$ and $P_{mus}(n)$ are real valued signals. The fact that $P_{mus}(n)$ creates the airway flow, $\dot{V}(n)$, and thus the basic force forming the pressure within the mask, $P_{aw}(n)$ means that R and C parameters have effects on $\dot{V}(n)$ and $V(n)$. In this study, we first obtain $P_{mus}(n)$ by filtering (eliminating) the components $\dot{V}(n)$ and $V(n)$ of $P_{aw}(n)$ signal. Then, using relevant $P_{mus}(n)$, we estimate the parameters R and C.

The measurement setup is shown in Figure 1. Respiratory signals ($P_{aw}(n)$ and $\dot{V}(n)$) and pulmonary volume ($V(n)$) have been produced by the artificial lung simulator (ASL 500, IngMar Medical, USA) according to the adjustable R, C and the highest $P_{mus}(n)$ (P_{mx}) parameter values, and measured by Pneumograph (RSS100HR, Hans Rudolph, USA) after passing through the human model (Laerdal Medical). 22 respiratory signals with the different R, C and P_{mx} values were acquired at a sampling frequency of 100 Hz with 16 bit precision (DAQCard-6036E, National Instruments, USA). Each of the respiratory signals consists of at least 10 cycles of expiration and inspiration periods.

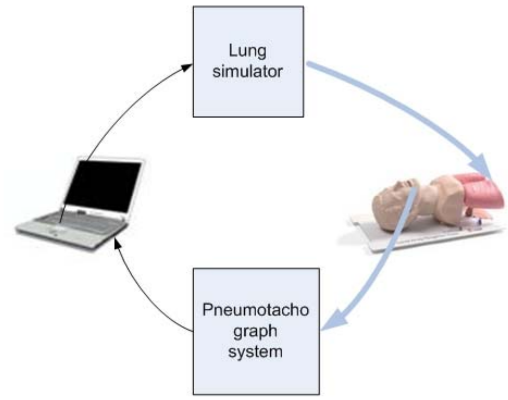

Figure 1: The measurement and acquisition setup of respiratory signals.

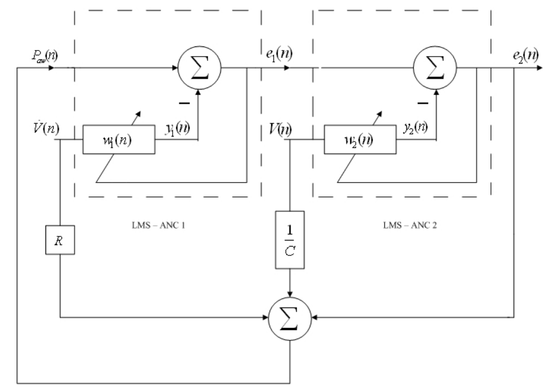

Figure 2: The filtering of $P_{aw}(n)$ with the cascade LMC-ANC filters.

3. ESTIMATION OF THE RESPIRATORY MUSCLE PRESSURE

In this study, we propose Least Mean Squares (LMS) based Adaptive Noise Canceler (ANC) filtering of inner mask pressure signal $P_{aw}(n)$ to eliminate the effects of airflow rate $\dot{V}(n)$ and the lung volume $V(n)$.

3.1 LMS based Adaptive Noise Canceler

The output signal $y(n)$ of the LMS filter can be defined as

$$y(n) = \mathbf{w}^T \mathbf{x}(n) + v(n) \quad 0 \leq n < N. \tag{2}$$

where $\mathbf{w} = [w_0, w_1, \cdots w_{M-1}]^T$ is the coefficient vector of the filter with length M, $\mathbf{x}(n) = [x(n), x(n-1), \cdots x(n-M+1)]^T$ is the input vector and $v(n)$ is the uncorrelated measurement noise. The main purpose to use LMS is to obtain $w(n)$ by using $y(n)$ and $x(n)$ signals.

ANC filter is a stochastic adaptive filter that can be used to eliminate a band limited (and non-white) additive noise $x'(n)$ from a signal $d(n)$. One of the inputs of ANC filter is the primary input signal, $d(n)$, and other one is the reference signal x(n) related to the additive noise. The output of ANC filter is named as the error signal $e(n)$ that is supposed to be the desired signal $d(n)$ without any noise component. The estimation of adaptive filter coefficients, which are essentially required, can be performed using LMS algorithm. In this case, the coefficients are updated by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e^H(n)\mathbf{x}(n) \tag{3}$$

where μ is the step size parameter and $e^H(n)$ is the complex conjugate of the error signal

$$e(n) = d(n) - y(n). \tag{4}$$

3.2 Application of LMS-ANC to $P_{aw}(n)$

In this study, two cascade LMS-ANC filters were used, as demonstrated in Figure 2. Elimination of the effects of airway flow, $\dot{V}(n)$ is provided by the first filter, whereas the second filter is used to eliminate the effects of the lung volume $V(n)$.

Primary input signal of the first filter (LMS-ANC1) is the mask pressure, $P_{aw}(n)$, and the reference signal of the filter is gas flow rate through airways $\dot{V}(n)$. Step size of the first filter is chosen as $\mu_1 = 0.001$ to meet $0 < \mu < 2/\lambda_{max}$ (here, λ_{max} is the largest eigenvalue of the correlation matrix, $\mathbf{R}$) in order to ensure the stability of coefficients [6]. The output error signal $e_1(n)$ of LMS-ANC1 gives the mask pressure signal, which have no, effect of the airway flow signal.

Primary input signal of the second filter, (LMS-ANC2) is the output error signal of the first filter, $e_1(n)$, whereas its reference signal is lung volume $V(n)$. Step size of the second filter is also $\mu_2 = 0.001$. The output error signal $e_2(n)$ of LMS-ANC2 in this case is the mask pressure signal, in which the effect of the lung volume are filtered off.

3.3 Determination of LMS-ANC filter length

Determination of lengths of the LMS-ANC filters has a great importance since it directly affects the performance of the filters. As an example, change in mean square error (MSE) of LMS-ANC1 filter has been derived for three different filter length as shown in Figure 3. MSEs have been calculated by the formula $J(n) = J_{\min} + J_{ex}(n)$ [6]. The smallest MSE value, $J_{\min}$ is given by

$$\begin{aligned} e_0(n) = &\ P_{aw}(n) - R \times \dot{V}(n) \\ J_{\min} = &\ e_0(n) e_0^H(n) \end{aligned} \tag{5}$$

The time-varying excess MSE, $J_{ex}(n)$ is calculated as

$$\begin{aligned} \mathbf{u} = &\ \begin{bmatrix} \dot{V}(M) & \cdots & \dot{V}(N) \\ \vdots & \ddots & \vdots \\ \dot{V}(1) & \cdots & \dot{V}(N-M+1) \end{bmatrix} \\ \mathbf{R} = &\ \mathbf{u}\mathbf{u}^H \\ \mathbf{c}(n) = &\ \mathbf{w}_0 - \mathbf{w}(n) \\ \mathbf{K}(n) = &\ \mathbf{c}(n)\mathbf{c}^H(n) \\ J_{ex}(n) = &\ tr[\mathbf{R}\mathbf{K}(n)]. \end{aligned} \tag{6}$$

As Figure 3 reveals, MSE takes its lowest value for the optimum filter length ($M_{op} = 5$). The theoretical information criterias such as Akaike Information Criteria (AIC) [6] and Minimum Description Length (MDL) [9] are widely used in the order estimation of autoregressive models. Since these decision methods are based on asymptotic assumptions, they

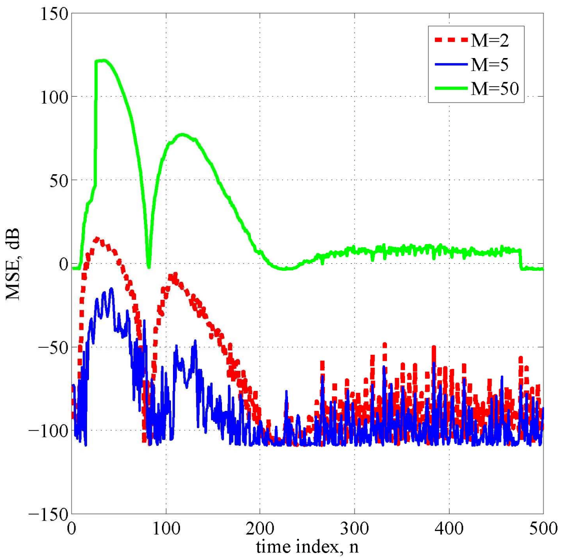

Figure 3: The effect of filter length on MSE of LMS-ANC filter. The curves also reveal the transition from inspiration to expiration periods. The optimal filter order is M_{op} is 5.

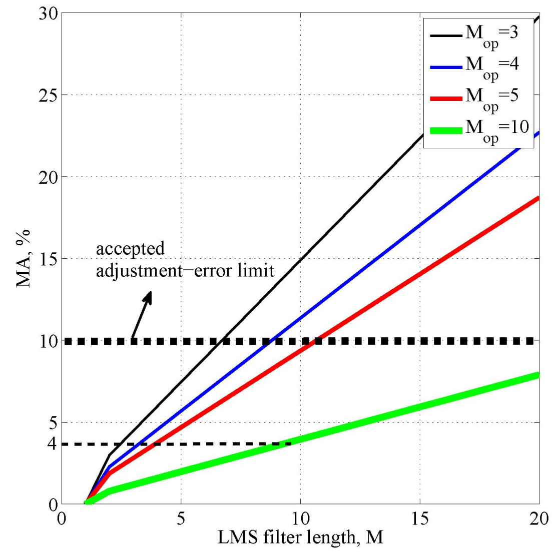

Figure 4: Adjustment error of LMS-ANC filter coefficients vs filter length.

can not be used for the problem in this study. Besides, the signals $\dot{V}(n)$ and $V(n)$ are non–white and highly correlated with the final output $e_2(n)$ of LMS-ANC filters which makes the estimation of optimal filter length a more challenging problem.

While the studies on estimation of filter lengths is still going on, Misadjustment (MA) is used as a criterion for determination of filter length for this study. In this method, using $\dot{V}(n)$ and $V(n)$ which has been whitened by adding N-point random noise ($\mu = 0, \sigma^2 = 0.01$), misadjustment is calculated using the approximation $MA \approx \frac{\mu}{2} \sum_{i=1}^{M} \lambda_i$ depending on MA filter lengths, [7]. Here λ_i denotes the ith eigenvalue of the autocorrelation matrix of the reference input signal.

In Figure 4, percentage adjustment error values of four different respiratory signals are demonstrated for different filter lengths. Measurements are calculated by using the respiratory signals with the same C and P_{mx} but different R values. It is observed that the mean adjustment error of LMS filter coefficients increase by increasing filter length. However, M_{op} within the acceptable adjustment–error limit (%10) [6] gives an adjustment error approximately by %4 when $M = M_{op}$. This method, by which the filter length of LMS-ANC is determined for the respiratory signals with only one variable parameter, revealed the effects of P_{mx} on the power spectrums of $V(n)$ and $V(n)$ signals.

4. ESTIMATION OF RESPIRATORY PARAMETERS, *R* AND *C*

The resulting output $e_2(n)$ of the LMS-ANC filters with the optimal filter length is the muscular pressure, $P_{mus}(n)$. The relationship between $P_{mus}(n)$ and the respiration parameters R, C is given by

$$\mathbf{Z} = \mathbf{H}\theta + \mathbf{r} \tag{7}$$

where $\mathbf{Z}$ and $\mathbf{r}$ are N element vectors, θ is n_θ element vector and $\mathbf{H}$ is a $N \times n_\theta$ matrix. The estimation of the parameter vector $\hat{\theta}$ is defined as

$$\hat{\theta} = \left(\mathbf{H}^{\mathbf{T}}\mathbf{R}_b^{-1}\mathbf{H}\right)^{-1}\mathbf{H}^{\mathbf{T}}\mathbf{R}_b^{-1}\mathbf{Z} \tag{8}$$

where $\mathbf{r} \sim N(0, \mathbf{R}_b)$. The variance of $\hat{\theta}$ is given by

$$\mathbf{P}_{\hat{\theta}} = \left(\mathbf{H}^{\mathbf{T}}\mathbf{R}_b^{-1}\mathbf{H}\right)^{-1}. \tag{9}$$

In our simulations for the BLUE algorithm, the matrices were defined as

$$\begin{aligned}
\mathbf{Z} &= \begin{bmatrix} e_2(0) & e_2(1) & \cdots & e_2(N-1) \end{bmatrix}^T \\
\theta &= \begin{bmatrix} R & 1/C \end{bmatrix}^T \\
\mathbf{H} &= \begin{bmatrix} \dot{V}(0) & V(0) \\ \dot{V}(1) & V(1) \\ \vdots & \vdots \\ \dot{V}(N-1) & V(N-1) \end{bmatrix}
\end{aligned} \quad . \tag{10}$$

5. EXPERIMENTAL RESULTS

Respiratory parameters in (1) were estimated by BLUE computed with (8) and covariance matrix is calculated by (9). The comparison of the estimated and true values (the values that are adjusted in the lung simulator) of the parameters R and C is summarized in Table1. The table also shows the error variances ($\mathbf{P}_{\hat{\theta}}$) and the LMS-ANC filter lengths that are selected according to MA criterion described in Section 3.3.

It is observed from the Table 1 that respiratory parameters were estimated consistently from the observed airway

Table 1: The comparison of adjusted and estimated respiratory parameters R and C. Units: R: $cmH_2O \cdot s \cdot l^{-1}$, C: $l^{-1} \cdot cmH_2O$, and P_{musmax}: cmH_2O.

Adjusted Respiration Parameters	Estimated R	C	Filter Length M_1	M_2
$R=3, C=0.1, P_{mx}=6$	3.78 (0.0007)	0.105 (0.49)	3	10
$R=4, C=0.1, P_{mx}=6$	4.70 (0.0009)	0.102 (0.59)	4	10
$R=5, C=0.1, P_{mx}=6$	5.55 (0.0001)	0.103 (0.73)	5	10
$R=10, C=0.1, P_{mx}=6$	10.22 (0.0003)	0.121 (1.24)	10	10
$R=15, C=0.1, P_{mx}=20$	15.06 (0.0006)	0.094 (0.34)	21	20
$R=20, C=0.1, P_{mx}=20$	20.69 (0.0001)	0.074 (0.89)	29	29
$R=30, C=0.1, P_{mx}=20$	29.70 (0.0001)	0.120 (0.68)	45	40
$R=3, C=0.1, P_{mx}=4$	3.77 (0.0002)	0.102 (1.32)	3	10
$R=3, C=0.1, P_{mx}=6$	3.80 (0.0007)	0.102 (0.52)	3	10
$R=3, C=0.1, P_{mx}=8$	3.77 (0.0004)	0.104 (0.27)	3	10
$R=3, C=0.1, P_{mx}=10$	3.75 (0.0003)	0.107 (0.18)	3	10
$R=3, C=0.1, P_{mx}=12$	3.70 (0.0002)	0.109 (0.13)	3	10
$R=3, C=0.05, P_{mx}=6$	4.88 (0.0001)	0.054 (4.57)	3	19
$R=3, C=0.07, P_{mx}=6$	4.05 (0.0008)	0.081 (1.29)	3	13
$R=3, C=0.08, P_{mx}=6$	4.03 (0.0008)	0.082 (0.99)	3	13
$R=3, C=0.09, P_{mx}=6$	3.88 (0.0007)	0.096 (0.66)	3	11
$R=3, C=0.1, P_{mx}=6$	3.79 (0.0007)	0.105 (0.50)	3	10
$R=3, C=0.11, P_{mx}=6$	3.73 (0.0007)	0.116 (0.38)	3	9
$R=3, C=0.12, P_{mx}=6$	3.66 (0.0007)	0.115 (0.37)	3	9
$R=3, C=0.15, P_{mx}=6$	3.56 (0.0006)	0.148 (0.16)	3	7
$R=3, C=0.2, P_{mx}=6$	3.47 (0.0006)	0.206 (0.07)	3	5
$R=3, C=0.25, P_{mx}=6$	3.43 (0.0005)	0.257 (0.04)	3	4

pressure, air flow rate and lung volume. Refering to the results in Table 1, the variances of the estimation error have small and specific ranges that are also independent from the adjusted parameters. In addition, it should be emphasized that the method for the selection of optimal LMS-ANC filter length can be applied in the cases where only one of the parameters is changed.

6. CONCLUSIONS

This study, in the trace of the studies conducted previously, aims at determining R and C parameters through a non-invasive method, which are among the important respiratory system parameters and needed to be measured by the clinical physicians in many cases. It should be also emphasized that this is a lung model study that has a targeted objective to be independent from any clinical condition. Application of the proposed method to the clinical data can be found in [10]. Although both estimated parameter values and estimator variances were shown to carry diagnostic characterizations, without estimation validations the results may have considered unreliable. LMS-ANC filter is well fitted to the determination of muscular pressure problem, however searching for the optimum filter length requires further investigation.

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