Biomedical Signal Processing and Control 39 (2018) 74–80

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Reducing bias in fractional order impedance estimation for lung function evaluation

Dana Copot [a,*], Robin De Keyser [a], Eric Derom [b], Manuel Ortigueira [c], Clara M. Ionescu [a]

[a] Department of Electrical Energy, Systems and Automation, Research Group on Dynamical Systems and Control (DySC), Ghent University, Belgium
[b] Department of Pulmonary Disease, Ghent University Hospital, Gent, Belgium
[c] UNINOVA and DEE/Faculdade de Cilncias e Tecnologia da UNL, Campus da FCT Quinta da Torre, Caparica, Portugal

ARTICLE INFO

Article history:
Received 12 December 2016
Received in revised form 15 May 2017
Accepted 20 July 2017
Available online 6 August 2017

Keywords:
Fractional order impedance
Respiratory function
Empirical mode decomposition
Lung function test
Filtering
Parametric model
Signal processing
Forced oscillation technique
Biomedical signal processing

ABSTRACT

Forced oscillation technique (FOT) emerged as a non-invasive, computationally efficient, fast and reliable method used in clinical practice for lung evaluation by means of fractional order impedance. Only recently, FOT has been employed to assess respiratory properties at low frequencies. When measuring at low frequencies interference between the imposed pressure oscillations and the breathing signal of the subject occurs. To deal with these challenges filtering techniques have been proposed to avoid biased correlates in the impedance, but none proved to successfully separate this disturbance signal. Hence, in this paper we are investigating the usefulness of empirical mode decomposition techniques to eliminate the bias introduced by the breathing signal. Respiratory data from patients diagnosed with chronic obstructive pulmonary disease (COPD) were analyzed and the results indicate that the method can successfully fill the gap in reducing the bias in the estimated impedance. The preliminary results show that by using the decomposed signals to estimate the fractional order impedance a bias reduction of respiratory impedance evaluation can be achieved.

1. Introduction

Interest in modeling and simulation of health care systems has increased in the last years and several approaches have been considered. This problem has not been tackled only from a patient model perspective (which is the aim of this paper) but also from a process point of view [1]. From the perspective of respiratory system frequency response function of the respiratory impedance has been broadly considered in the last decades [2,3]. Its importance lies in the fact of being evaluated by means of non-invasive techniques, such as the forced oscillation (FOT) method. Briefly, the FOT principle is based on superimposing a pressure signal on the spontaneous breathing of the subject [2]. Novel tools for processing and analysis of the human respiratory system have brought a significant contribution to the progress in this interdisciplinary area [2,4,5]. There is an increased interest on evaluating the respiratory impedance at low frequencies [6,7] since viscoelasticity becomes a key factor at these frequencies in patient diagnosed with obstructive respiratory diseases (e.g. chronic obstructive pulmonary disease).

When measuring the respiratory impedance using FOT technique a load at the mouth of the patient is imposed [8] which introduces nonlinear distortions in the signal sent to the patient [9]. Moreover, additional nonlinear effects from the respiratory tissue may appear. Although the dynamic response of the lungs is considered linear this does not mean that during measurement only the linear effects are captured. Since we are now focusing on low frequencies measurements, nonlinearities are even more prominent due to the rheological effects. Hitherto, only few works have been reported to assess the nonlinear contributions from the measured signals [10–12].

The bottleneck in terms of respiratory impedance estimation at low frequencies is the non-stationary signal of the breathing. Once this issue is solved the added value of the FOT in clinical practice could be recognized. In this paper, we address this problem from a filtering technique point of view. First, empirical mode decomposition techniques have been applied to solve the problem of bias in the measured data. Second, best linear approximation techniques are used to determine the non-linear contributions from both device and tissue. Therefore, we propose here a tailored version of the EMD for estimating respiratory impedance on the best linear approximation [13]. This method has been applied in several areas of research [12], but there is less evidence in applying this

* Corresponding author.
E-mail address: dana.copot@ugent.be (D. Copot).

http://dx.doi.org/10.1016/j.bspc.2017.07.009
1746-8094/

method on real physiological signals. Hence, the originality of this work it goes one step forward and is filling the gap of reducing the bias due to interference of the breathing signal. Hitherto, there is not much evidence on the use of the EMD method on real physiological signals [14]. In this paper real respiratory signals recorded using FOT techniques are being investigated. The aim of this work is to explore if minimization of the bias in respiratory impedance for lung function evaluation can be achieved. For this the EMD method is applied to recorded signals (i.e. pressure and flow) and the results obtained are presented in Section 3. In this paper it has been shown that the EMD algorithm can be successfully applied for real signals. Moreover, the use of EMD in combination with the best linear approximation method gives the best results in terms of bias reduction of respiratory impedance.

The structure of the paper is as follows: In Section 2 the materials and methods are presented. Here a description of the device and an overview of the subjects is given followed by a theoretical background on nonlinear contributions, empirical mode decomposition and fractional order impedance. The results are presented in Section 3. A conclusion section summarizes the main outcome of the study.

2. Materials and methods

2.1. Device and measurements

A standard forced oscillation technique device delivers air pressure oscillations into the respiratory system during tidal breathing. Commercially available devices use a loudspeaker in order to generate the pressure oscillations between 4 and 48 Hz, which means that reliable oscillation can be only created as low as 4 Hz. To circumvent this limitation, a house-made prototype device has been developed in our research group (see Fig. 1). With this prototype reliable pressure oscillations by means of ventilators as low as the breathing frequency (≈0.3 Hz) can be created [10]. A pushing fan draws fresh air into the devices and creates pressure oscillations which are guided through straws towards the respiratory system of the patient. The air expired by the patient is drawn out of the device by the pulling fan. This is achieved by means of a pulse wave modulated signal and pressure oscillations with an amplitude between 0.1 and 0.3 kPa (peak-to-peak). These values are set for the patient's safety and remain within linear conditions for impedance estimation algorithms. The pressure (P) and airflow (Q) of the subject are measured by means of pressure sensors and pneumotachograph.

In Fig. 1 photo of the FOT device and related instrumentation is given. The classical manner for impedance Z_r (kPa s/l) estimation is to consider a linear relation between the breathing signals and the imposed pressure oscillations at the mount of the subject [4]. By electrical analogy, one may consider that the voltage is represented by the pressure and the current is represented by the flow. Next, the impedance of the respiratory system Z_r can be derived by means of spectral analysis (i.e. frequency domain):

$$Z_r(j\omega) = \frac{S_{PU(j\omega)}}{S_{QU(j\omega)}} \tag{1}$$

with U the input signal, $S(j\omega)$ represents the cross-correlation spectra between input–output signals, ω (rad/s) is the angular frequency and $j = \sqrt{-1}$ resulting in a complex variable evaluated in each frequency point of interest [15]. Time response of linear transfer function approximations can then be further analysed.

In Fig. 2 the desired pressure (red dashed line, upper graph) and the measured pressure (blue continuous line, upper graph) with the corresponding flow (middle graph) and the excitation signal (lower graph) are represented. Observe in middle graph the low frequency of the breathing of the volunteer. The input signal shown in the lower graph represents a small amplitude pressure oscillations applied to the patient during spontaneous breathing.

However, to analyze the nonlinear effects from the side of the patient as well as from the side of the device best linear approximation (BLA) method has been applied. This method has been proven to be successful for this application [3]. Therefore, by means of BLA one can determine the variance of non-linear distortions and noise [3]. A detailed overview of these methods as well as other examples are given in [10,16].

Patients: The study includes patients diagnosed with COPD who came for periodic evaluation of their lung function at Ghent University Hospital, Belgium. Written informed consent was obtained from all subjects. This study and the consent procedure has been approved by the local ethical committee of Ghent University Hospital, Ethical advice number B670201111936.

2.2. Empirical mode decomposition (EMD)

EMD is a method to decompose a given signal into a set of elemental signals called *intrinsic mode functions* (IMFs) [17–19]. EMD is the basis of Hilbert–Huang transform (HHT) which comprises the EMD and the Hilbert spectral analysis followed by an instantaneous frequency computation. The added value of this method is the introduction of IMF based on local properties of the signal. This method is a suitable approach for analysis of sinusoidal signals, as the recorded signals used in this analysis. For a signal to be considered as an IMF, the following conditions have to be accomplished: (i) the number of maxima and minima and the number of zero-crossings has to be equal; and (ii) the local mean, expressed as the mean of upper and lower envelopes, has to be zero. By analyzing the evolution of a signal $x(t)$ between two consecutive local extrema one may determine a high-frequency section, which can be also represented as a *detail* ($d(t)$). By identifying the low-frequency section $w(t)$ one has the following: $x(t) = w(t) + d(t)$. Considering that the procedure is followed in a proper manner for all the oscillations, the IMFs can be obtained. Considering a signal $x(t)$, the EMD methodology can be briefly described as [17]:

1 identify all extrema of $x(t)$;
2 interpolate between minima and maxima in order to obtain the lower envelope ($e_{min}(t)$) and the upper envelope ($e_{max}(t)$);
3 compute the mean envelope $w(t) = (e_{\min}(t) + e_{\max}(t))/2$;
4 extract (local) high-frequency section (i.e. the detail) $d(t) = x(t) - w(t)$;
5 iterate on the residual $w(t)$.

For a given signal $x(t)$, EMD result has the following form:

$$x(t) = w_K + \sum_{k=1}^{K} d_k(t) \tag{2}$$

with $w_K(t)$ the residual trend; $d_k(t)$ the modes, with k=1,. . ., K being constrained to be zero-mean amplitude/frequency modulation waveforms. EMD is an effective method for cases where sinusoidal models are being considered (such as the signal used in this investigation) [17]. Considering a double side band modulated sinusoid function such as $g(t)=A(t)sin[(\phi)(t)]$, for this case even when $A(t)$ is a sinusoid the generated result it is not an IMF. However, one can say that a function of the type $A(t)sin[\phi(t)]$ can be characterized as an IMF, if $A(t)$ is a slowly varying function (this is the so-called envelope).

However, in real life applications the procedure described above has to be redesigned by implementing a shifting process. More specifically to iterate steps 1–4 until the detail signal $d(t)$ can be considered as zero-mean. At the moment this is achieved the detail is considered as an IMF and then the computation of the residual occurs and step 5 can be applied. With every IMF calculated