EXPLORING THE ADVANTAGES OF BLIND SOURCE SEPARATION IN MONITORING INPUT RESPIRATORY IMPEDANCE DURING APNEIC EVENTS

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Abstract: *In this contribution, we investigate the effectiveness of using filtering techniques based on blind source separation methods for continuous monitoring of input respiratory impedance to detect obstructive sleep apnea (OSA). The simple and non-invasive forced oscillation lung function test is used to apply respectively a 1Hz and a 3Hz input pressure oscillation to the patient during spontaneous ventilation. Once the breathing signal extracted by means of independent component analysis (FastICA) method, the input respiratory impedance can be obtained by the ratio between respiratory pressure and flow at the excited frequency. This index is then used to detect changes in the respiratory impedance values as a result of the apneic events. The advantages of the blind source separation techniques are emphasized and its use to assess respiratory mechanics for detecting OSA episodes is extracted from this study.*

Keywords: *biomedical signal processing, amplitude modulation, independent component analysis, filter, respiration, respiratory impedance*

1. INTRODUCTION

Obstructive sleep apnea syndrome (OSAS) is defined as recurrent episodes of partial or complete upper airway obstruction, commonly associated with intermittent hypoxia and sleep fragmentation [10]. It is therefore important to monitor the airway mechanics by measuring the input respiratory impedance as a detection index of apneic events [1,11,12]. Respiratory mechanics are efficiently assessed using non-invasive lung function tests such as the forced oscillation technique (FOT), due to their advantage of requiring solely the tidal breathing of the patient (no forced manoeuvers, thus can be applied during sleep studies) [7]. The overall aim of this contribution is to assess the effectiveness of using blind source separation methods for signal processing of the respiratory impedance. One of the most common blind source separation methods nowadays is the independent component analysis (ICA), which proved to be a fast and reliable filtering method in other biomedical applications [3,6,9]. The choice of this method lies in its well-tolerated applicability in filtering biological signals and low computational cost (FastICA) [4,5]. Forced Oscillation technique is generally used in sleep

studies, by use of continuous positive airway pressure (CPAP) applied to patient suffering from sleep apnea/hypopnea syndrome. The FOT provides a non-invasive measure of the airway obstruction. A manifold of studies have been performed in the past [1,11,12], providing useful clinical insight upon the use of FOT and optimal CPAP delivery rates. However, if the breathing-frequency of the patient changes significantly over the time, standard filtering techniques cannot be applied due to their non-adaptive nature and if the frequencies of the input and the breathing are very close to each other, overlapping, a filter separation will not give reliable results.

A study on ICA blind source separation algorithms is given in this contribution with the purpose to provide a continuous monitoring of the respiratory impedance. In order to illustrate the impossibility to use standard filters, two specific scenarios are presented, along with experimental tests. Two examples are presented, in which a 1Hz and respectively a 3Hz sinusoid is superimposed on the breathing of the patient (breathing cycle 4s). The forced oscillation device and FOT method along with a brief overview upon the blind source separation algorithm is given in the next section. The results are then discussed and the conclusion section summarizes the main outcome of this study.

2. MATERIALS AND METHODS

2.1 Respiratory input impedance measurement

The impedance was measured using the FOT standard setup, commercially available, assessing respiratory mechanics from 4-48Hz. An I2M (Input Impedance Measurement) device has been used for pulmonary testing. The specifications of the device are those of commercially available i2m devices: 11kg, 50x50x60 cm, 8 sec measurement time, European Directive 93/42 on Medical devices and safety standards EN60601-1. Because the standard measurement time (8 seconds) is too short, a second measurement line has been connected to a data acquisition PCMCIA card and the signals recorded for 30 seconds, in order to provide better estimates. The subject is connected to the typical setup from figure 1 via a mouthpiece, suitably designed to avoid flow leakage at the mouth and dental resistance artefact. The oscillation pressure is generated by a loudspeaker (LS) connected to a chamber [7]. The LS is driven by a power amplifier fed with the oscillating signal generated by a computer (**U**). The movement of the LS cone generates a pressure oscillation inside the chamber, which is applied to the patient's respiratory system by means of a tube connecting the LS chamber and the antibacterial filter (bf). A side opening of the main tubing (BT) allows the patient to have fresh air circulation. Ideally, this pipeline will have high impedance at the excitation frequencies to avoid the loss of power from the LS pressure chamber. The measurements of air-pressure **P** and air-flow **Q** (= $\dot{\mathbf{V}}$, with **V** - air volume) during the FOT lung function test is done at the mouth of the patient.

The testing protocol was to leave the patient breath normally while receiving the excitation sinusoid from the FOT device for 30 seconds and in this time interval we asked to hold breath for several seconds, at a moment which was decided by the patient. This then simulated closely a normal breathing with an apneic event.

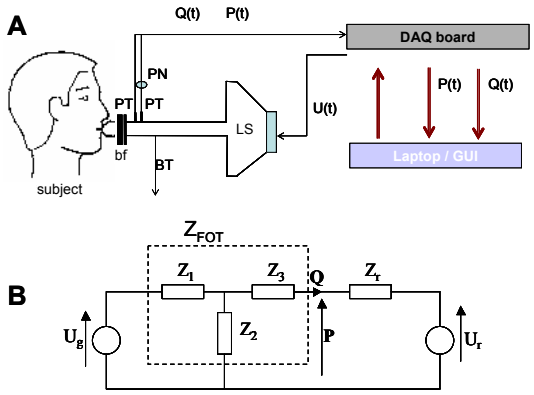

Fig. 1. A: schematic overview of the FOT device and **B:** equivalent electrical scheme. Notations apply: A - amplifier; LS - loudspeaker; BT - bias-tube; PN - pneumotachograph; bf - antibacterial filter; PT - pressure transducer; $Q(t)$ - flow; $P(t)$ - pressure; $U_g(t)$ - driving signal; $U_r(t)$ - breathing.

2.2 The blind source separation problem

Typically, the *blind source separation* problem can be explained via the *cocktail party problem*: two people are speaking simultaneously in a room where two microphones record in different locations time signals, denoted by $\mathbf{x}_1(t)$ and $\mathbf{x}_2(t)$, with x_1 and x_2 their amplitudes, and t the

time index. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, consequently denoted $\mathbf{s}_1(t)$ and $\mathbf{s}_2(t)$. The linear equation results:

$$\begin{aligned}\mathbf{x}_1(t) &= a_{11}\mathbf{s}_1(t) + a_{12}\mathbf{s}_2(t)\\ \mathbf{x}_2(t) &= a_{12}\mathbf{s}_1(t) + a_{22}\mathbf{s}_2(t)\end{aligned} \quad (1)$$

where a_{11}, a_{12}, a_{21}, and a_{22} are parameters depending on the distances between the microphones and the speakers. It would be very useful to estimate the two original speech signals $\mathbf{s}_1(t)$ and $\mathbf{s}_2(t)$, using only the recorded signals $\mathbf{x}_1(t)$ and $\mathbf{x}_2(t)$. In this work, the freely available FastICA algorithm is used to estimate source signals one of the sinusoid that come from the FOT device, the other being the breathing signal $U_r(t)$ of the patient. Both signals are linearly mixed (superposition) at the entrance tube and recorded by two transducers located at two different places (recall figure 1). The recorded signals can be modelled by using the linear model defined by:

$$\boldsymbol{x = As} \quad (2)$$

where x is recorded signal vector, A is the unknown mixing matrix and s is source vector. The goal of the FastICA algorithm is to estimate the original sources s as given only the observations x. The estimation of the independent sources y is done by means of demixing matrix as follows:

$$\boldsymbol{y = Wx = WAs} \quad (3)$$

where $\boldsymbol{W = A^{-1}}$. However the exact order or scale the sources is never recovered exactly, so the demixing matrix has the form $\boldsymbol{W = PDA^{-1}}$, where P is a permutation matrix and $\boldsymbol{D = diag(d_1, d_2, ..., d_n)}$ is a diagonal matrix for arbitrary scaling. From this equality, **I** could be expressed as:

$$\mathbf{I} = \mathbf{WA} \quad (4)$$

where **I** must be the identity matrix. However, due to the fact that $\mathbf{A}^{-1} \cong \mathbf{W}$ is only an approximation, we can only find an approximation for **I**. The ICA algorithm constructs **w** such that it maximizes nongaussianity of $\mathbf{w}^T\mathbf{x}$, where **w** is a n-dimensional (weight) vector constrained so that $\mathrm{E}\{G(\mathbf{w}^T\mathbf{x})^2\} = 1$ with G any nonquadratic function. This **w** would correspond to a **I** with only one non-zero component. This would mean $\mathbf{w}^T\mathbf{x} = \mathbf{I}^T\mathbf{s}$ equals one of the actual sources, **s**. Note that the basic ICA algorithm requires a preliminary sphering or whitening of the data **x**. This means that the original observed variable is linearly transformed to a variable $\mathbf{x} = \mathbf{Q}v$ such that the correlation matrix of x equals unity: $E\{\mathbf{x}\mathbf{x}^T\} = \mathbf{I}$. The algorithm is simplified to the well-known ICA fixed-point algorithm [4,5]:

$$\begin{aligned}\mathbf{w}^+ &= \mathrm{E}\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - \mathrm{E}\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}\\ \mathbf{w}^* &= \mathbf{w}^+ / \left\|\mathbf{w}^+\right\|\end{aligned} \quad (5)$$

To ameliorate the uncertainty of the Newton method to convergence, a step size is added in (5), obtaining a stabilized fixed-point algorithm:

$$\begin{aligned}\mathbf{w}^+ &= \frac{\mathbf{w} - \mu[\mathrm{E}\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - \beta\mathbf{w}]}{[\mathrm{E}\{g'(\mathbf{w}^T\mathbf{x})\} - \beta]}\\ \mathbf{w}^* &= \mathbf{w}^+ / \left\|\mathbf{w}^+\right\|\end{aligned} \quad (6)$$

where $\beta = E\{\mathbf{w}^T\mathbf{x}g(\mathbf{w}^T\mathbf{x})\}$ is the same as above, and μ is step size parameter that may change with iteration count. Taking μ much smaller than unity (say 0.1 or 0.01) helps the algorithm to converge; in our case, μ was set to 0.01.

2.3 Identification methods

Assuming that the excitation signal is not correlated with the breathing of the patient [2] one can estimate the respiratory impedance as:

$$Z_r(j\omega) = \frac{S_{PU}(j\omega)}{S_{QU}(j\omega)} \quad (7)$$

whereas the **P** corresponds to pressure (its electrical equivalent is voltage) and **Q** corresponds to air-flow (its electrical equivalent is current). Therefore, the respiratory impedance $\mathbf{Z_r}$ can be defined as the spectral (frequency domain) ratio between pressure and flow, with $S_{ij}(j\omega)$ the cross-correlation spectra between the various input-output signals, ω is the angular frequency and $j = (-1)^{1/2}$, resulting in a complex variable. In the case of monitoring the respiratory impedance, only the absolute value $|Z|$ is necessary to be estimated.

3. RESULTS

In both experiments, along with the pressure $P(t)$ and flow $Q(t)$, the driving signal $U_g(t)$ is acquired at a sampling frequency of 500Hz, as depicted in figure 2. One can observe the apneic events in which the air-flow is zero. By use of the ICA algorithm, the breathing signal is

extracted and analyzed from the measured air-pressure and air-flow, as depicted in figure 2 lower plots.

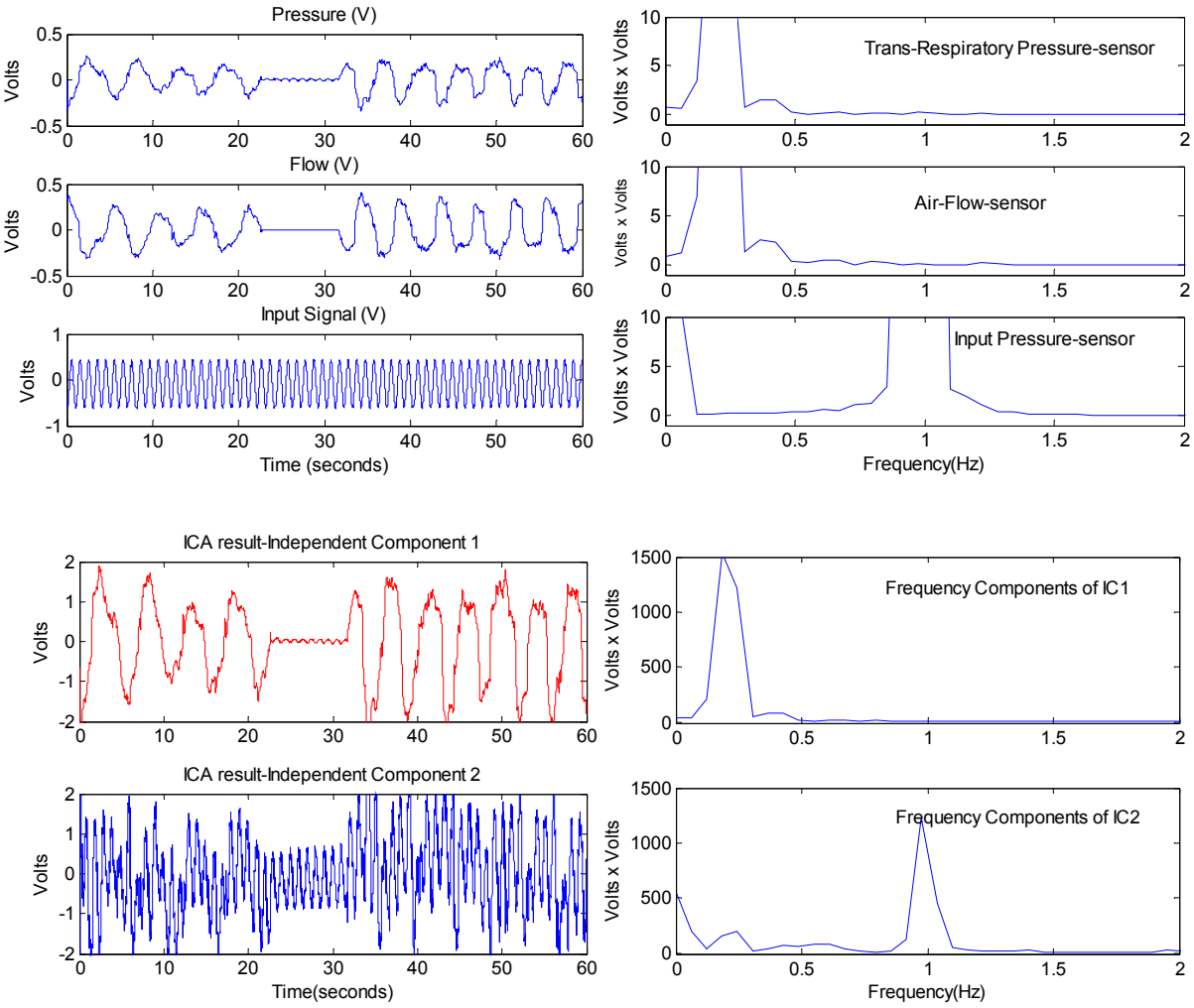

Fig. 2. Upper plots: recorded signals (left) along with their power spectral density functions (right) for the 1Hz input sinusoid. Similar signals apply for the 3Hz input sinusoid as well. Lower plots: ICA results (left) with breathing component (upper-left plot) along with their power spectral density functions (right).

Since FOT provides a direct measure of the respiratory impedance $|Z|$, and increased airway obstruction leads to increase in values of $|Z|$, this index is broadly used in artificial ventilation [1]. In the examples discussed in this study, the respiratory impedance can be obtained online for monitoring purposes by applying the signal processing scheme of figure 3. Given the measurements of air-pressure and air-flow and the breathing signal separated by the ICA algorithm, one can subtract these signals and the ratio of pressure and flow gives respiratory impedance (see figure 4). The use of additional filters ensures better quality of the resulted signal.

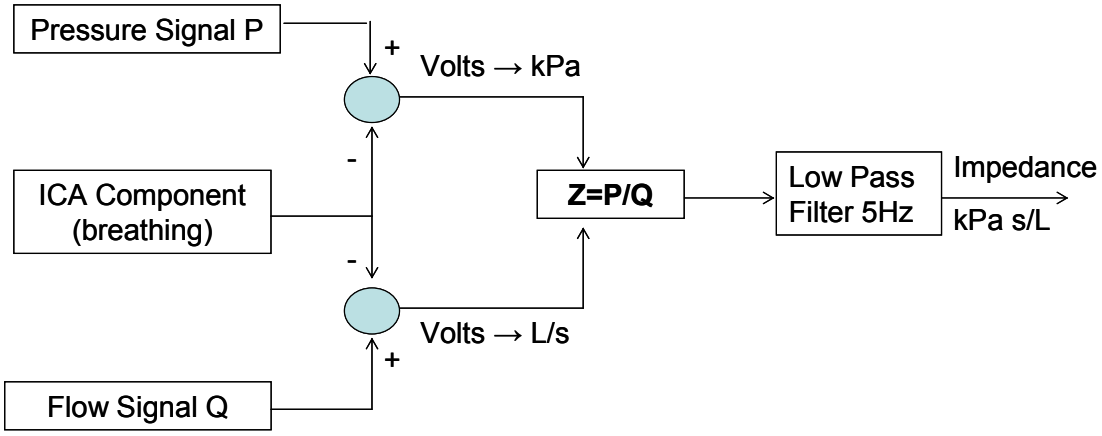

Fig. 3. Schematic representation of the procedure to obtain the respiratory impedance

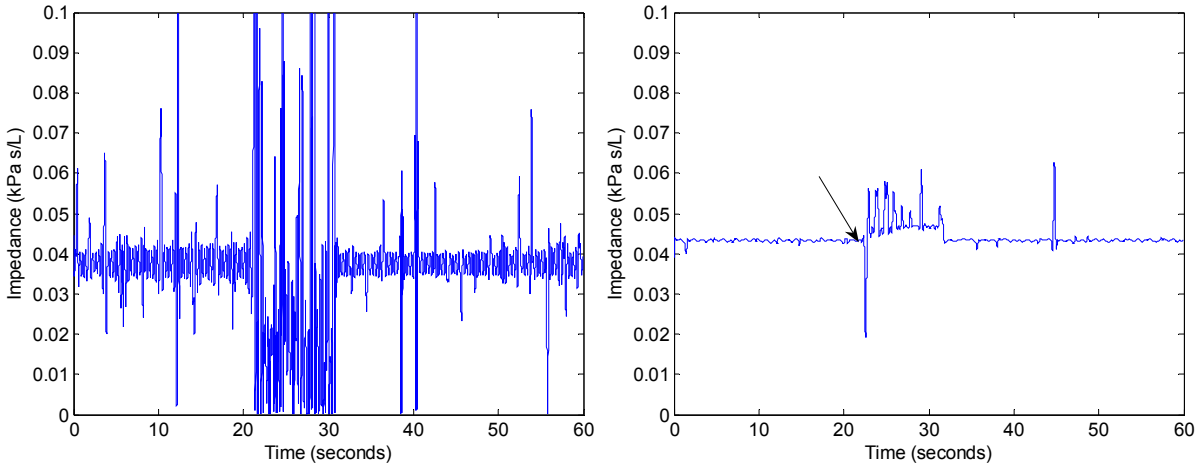

Fig. 4. Respiratory impedance for 1Hz (left) and for 3. Arrows indicate upper airway obstruction.

4. DISCUSSION

In both cases, the ICA algorithm can separate without problems the respiratory signal (breathing) and the excitation signal. In the case of 1Hz sinusoidal excitation, the low signal-to-noise ratio provides a lower quality in the filtered signal. However, it can be observed from the corresponding spectral analysis in frequency domain that the main energy is indeed coming from the two separated sources: around 0.25Hz for the breathing and 1Hz, respectively 3Hz for the excitation signal from the FOT device.

Let us take a closer look at the ICA –resulted breathing signal depicted in figure 2. Firstly, due to the fact that the respiratory system is nonlinear, harmonics of the breathing frequency are introduced as:

$$U_r(t) = A\sin 2\pi f_b t \tag{8}$$

with $f_b = 0.25Hz$, and harmonics multiple of the input frequency: $k * f_b$, with k=1,2,… These frequencies are observed in the spectral power density plot at 0.4Hz and 0.8Hz. Because the energy of the breathing signal is much bigger than the energy of the input oscillation from FOT, the ICA procedure can make a better approximation of the breathing component. A second observation is that a change in the amplitude of the remaining component is visible in the time domain (lower figure 2 left). It is often the case that nonlinear biological systems induce nonlinearities such as amplitude modulation. According to the theory of amplitude modulation, this frequency then must appear at $f_{in} \pm f_b$, with f_{in} the carrier frequency. A reconstruction of the excitation signal is performed then using demodulation

techniques. Assuming that the modulating signal has the f_m frequency, then the AM signal can be written in the form:

$$s_m(t) = (A + b\sin\omega_m t)\sin(\omega_{in} t + \alpha) \tag{9}$$

where:

- ✓ A is a positive constant (the DC component of the modulating signal);
- ✓ $\omega_{in} = 2\pi f_{in}$ with f_{in} the 'carrier' frequency, in this case 1Hz or 3Hz; and α its corresponding phase shift;
- ✓ $\omega_m = 2\pi f_m$ with f_m the modulating frequency.

Denoting $s(t) = b\sin\omega_m t$, we can observe that $|s(t)| < A$ for all t, thus $[s(t) + A]$ never goes negative. We investigate the effect of squaring the signal [8]:

$$s_m^2(t) = \left[(A + b\sin\omega_m t)\sin(\omega_{in} t + \alpha)\right]^2 = \\ = \left[A + b\sin\omega_m t\right]^2 \sin^2(\omega_{in} t + \alpha) \tag{10}$$

$$= \left[A + b\sin\omega_m t\right]^2 \frac{1 - \cos(2\omega_{in} t + \gamma)}{2} = \\ \frac{\left[A + b\sin\omega_m t\right]^2}{2} - \frac{\left[A + b\sin\omega_m t\right]^2 \cos(2\omega_{in} t + \gamma)}{2} \tag{11}$$

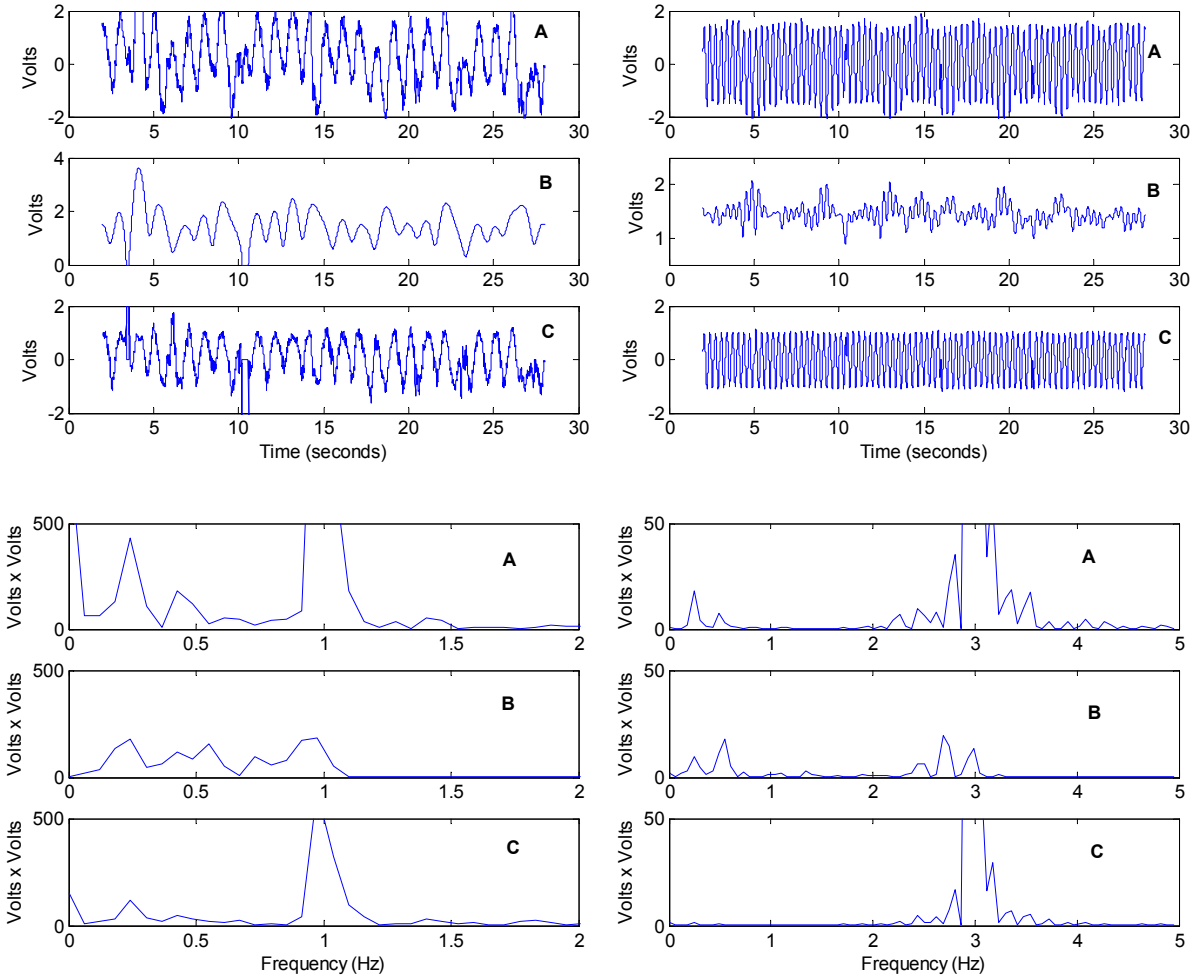

Fig.5. Upper plots: result of demodulation in time domain for the 1Hz carrier sinusoid (left) and for the 3Hz

From (11) the signal $0.5\left[A + b\sin\omega_m t\right]^2$ can be extracted by low-pass filtering (6th order Butterworth filter) as frequencies do not overlap. Left-hand term contains the 0, ω_m and $2\omega_m$ frequencies, while the right-hand term contains the $2\omega_{in}$, $2\omega_{in} \pm \omega_m$ and $2\omega_{in} \pm 2\omega_m$ frequencies. It is possible to take the positive square root of the 1st term, obtained after LPF, in order to get $0.707|s(t) + A|$. Taking the magnitude $|\ldots|$ of a signal represents a severe form of distortion, but it was already stated that

A is larger than the amplitude of *s(t)* so that $s(t)+A$ never goes negative. In that case, the magnitude $|s(t)+A|$ is equal to $s(t)+A$ and demodulation is accomplished, as depicted in figure 5. The frequency components of each of the processed modulation signals are depicted in figure 5, where one may notice frequencies as expected from (11).

5. CONCLUSIONS

In this contribution, specific (realistic) examples have been studied for use in monitoring respiratory impedance during sleep studies, to detect apneic events. Several advantages of the blind source separation method over the classical filtering techniques can be summarized as:

- no need for defining a cut-off frequency for the separation, thus the extraction can be performed even if the energy of the breathing signal is shifting in frequency with time (which is usually the case);
- can be easily applied online for continuous estimation due to low computational complexity;
- additionally, the breathing of the patient is monitored along with its respiratory impedance;
- provides signal enhancement.

Nonlinear effects of the respiratory system have been observed, namely amplitude modulation, containing frequencies related to tidal breathing.

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