Respiratory Rate Detection by Empirical Mode Decomposition Method Applied to Diaphragm Mechanomyographic Signals

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Abstract— **Non-invasive evaluation of respiratory activity is an area of increasing research interest, resulting in the appearance of new monitoring techniques, ones of these being based on the analysis of the diaphragm mechanomyographic (MMGdi) signal. The MMGdi signal can be decomposed into two parts: (1) a high frequency activity corresponding to lateral vibration of respiratory muscles, and (2) a low frequency activity related to excursion of the thoracic cage. The purpose of this study was to apply the empirical mode decomposition (EMD) method to obtain the low frequency of MMGdi signal and selecting the intrinsic mode functions related to the respiratory movement. With this intention, MMGdi signals were acquired from a healthy subject, during an incremental load respiratory test, by means of two capacitive accelerometers located at left and right sides of rib cage. Subsequently, both signals were combined to obtain a new signal which contains the contribution of both sides of thoracic cage. Respiratory rate (RR) measured from the mechanical activity (RR_{MMG}) was compared with that measured from inspiratory pressure signal (RR_P). Results showed a Pearson's correlation coefficient (r = 0.87) and a good agreement (mean bias = -0.21 with lower and upper limits of -2.33 and 1.89 breaths per minute, respectively) between RR_{MMG} and RR_P measurements. In conclusion, this study suggests that RR can be estimated using EMD for extracting respiratory movement from low mechanical activity, during an inspiratory test protocol.**

I. INTRODUCTION

Mechanomyographic (MMG) signal is a non-invasive recording of the mechanical activity of skeletal muscles during contraction. Considered to be the mechanical counterpart of electrical activity of muscles, MMG signal reflects the lateral vibration of muscle fibers, and represents an alternative and a complementary tool for the study of muscles [1]. It has been studied in several muscles by means of accelerometers, piezoelectric sensors, laser distance sensors and microphones [2]. On the other hand, the diaphragm, a dome-shaped sheet of muscle, which separates the thoracic and abdominal cavities, plays an important role in the respiratory function. The diaphragm mechanomyographic (MMGdi) signal is composed by a high frequency (HF) and a low frequency (LF) component. HF component, in a range of 5-25Hz [3], contains muscle vibration during a contraction and represents the diaphragm muscle fiber activation during inspiration. The LF component, in a range of 0-5Hz, represents the excursion of the thoracic cage during respiration due to the diaphragm contraction. LF component, modulated in amplitude and frequency, has proven to be useful for monitoring and extracting information from respiratory movements, in medical [4] and smartphone applications [5]. However, as well as many other biomedical signals, LF component can be corrupted by different sources of noise [6] and movement artifact [7], reducing its visual and automated analysis. Additionally, different morphologies have been observed in the LF component, which affects the evaluation of breathing patterns [8].

Several techniques have been proposed to filter and smooth the LF component in order to reduce non-desired interferences. Hung et al. [9] estimated the respiratory waveform collected from a bi-axial accelerometer located in the chest in two subjects while they were sitting and lying. The spectrum of 1-min segment was calculated and then band-pass filtered using a set of rules around the peak frequency. In other related work, Pechprasarn and Pongnumkul [5] measured respiratory rate (RR) in one subject lying down using a smartphone placed over the chest. The respiratory signal was smoothed, detrended, the power spectrum was calculated and finally the peak frequency was obtained as an estimation of RR. In this line, Aoude et al. proposed a method for detection of pause, movement artifacts and asynchrony in uncalibrated inductance plethysmography (RIP) data from 19 post-surgery infants [7].

The main filtering step used a bank of selective elliptic filters each with a 0.2 Hz pass-band and covering a range from 0 to 2 Hz. That filter that exhibited the highest power was chosen and then the breathing frequency corresponding to its central frequency was obtained.

In the present study, a method based on the empirical mode decomposition (EMD) [10] is applied. The EMD algorithm does not make an a priori assumption about the signals and therefore, it is suitable for the analysis of nonlinear and nonstationary time-series. It has been designed to adaptively decompose the signal into a set of oscillatory components called intrinsic mode functions (IMFs). IMFs represent the oscillation modes embedded in the data (modulated in amplitude and frequency). IMFs are similar to trigonometric terms and wavelet coefficients obtained by Fourier and Wavelet analysis, respectively. In a previous

L. Estrada was supported by Instituto para la Formación y Aprovechamiento de Recursos Humanos and Secretaría Nacional de Ciencia, Tecnología e Innovación (IFARHU-SENACYT Program) from the Panama Government under grant 270-2012-273. This work was supported in part by Ministerio de Economía y Competitividad from the Spain Government under grant TEC2010-21703-C03-01.

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work of the group [11], Torres et al. analyzed MMGdi signals in an animal model, demonstrated that the first IMFs captured fast oscillations related to the HF vibratory activity of diaphragm muscle while respiratory movement LF component were concentrated in lasts IMF components. In this perspective, the approach of the present study is to apply EMD to MMGdi signals acquired with two single-axis capacitive accelerometers placed on the chest, in both hemidiaphragms, in order to obtain the LF component and estimate the respiratory rate.

II. Material and Methods

A. Signal recording and preprocessing

Measurements were taken in a healthy, non-smoking subject, with no relevant medical history of respiratory disease. Prior to participation written consent was obtained from the subject and with the approval of Ethics Committee of Hospital del Mar, Barcelona. The MMGdi signal was recorded using two uni-axial capacitive accelerometers (K-Beam 8312B2, Kistler, Switzerland), placed on the left (MMGdiL) the right (MMGdiR) sides of the thoracic cage, between the seventh and eighth intercostal space and lateral to the midclavicular line. Simultaneously, inspiratory pressure (IP) was acquired by means of a pressure transducer (Digima Premo 355, Special Instruments, Germany). Data were collected using a data acquisition system (MP100, Biopac Systems, Santa Barbara, CA, USA) at a sampling rate of 2 kHz, amplified, filtered, analogue to digital converted (12bit resolution) and then further decimated at a sampling rate of 200 Hz. Furthermore, to obtain the low frequency component of respiratory activity, MMGdi signals were low-pass filtered using a zero-phase fourth-order, Butterworth filter with a cut-off frequency of 5 Hz.

B. Respiratory protocol

The subject was seated during the study and asked to breathe through a mouthpiece tube, while nostrils were occluded by a nose clip. Thereafter, the subject was instructed by the medical staff to breathe continuously and deep at a constant rate. During inspiration, increments in the IP signal (~10 cm H_2O) were generated by the addition of weights (~50 g) to a valve every two-minute interval. In exhalation, there was not occlusion of the tube and the subject could normally breathe out. The increment in the IP can be translated into changes in the respiratory muscle effort.

C. Empirical Mode Decomposition

Introduced by Huang et al., EMD is an adaptive method developed specially for the analysis of nonlinear and nonstationary signals [10] which has found application in biomedical data processing [12]. Without prior knowledge of the signal, EMD iteratively decomposes it into a set IMFs, which are amplitude and frequency modulated functions. Additionally, IMFs can be interpreted as a filter bank structure similar to that obtained via wavelet decomposition. By definition, an IMF must satisfy two conditions [10]:

a) The number of extrema and the number of zero-crossing must be either equal or differ at most by one in the whole data set.

b) At any point, the mean value of the envelope defined by local maxima and the envelope defined by local minima is zero. Briefly, the procedure involved in the EMD given a $x(t)$ signal is as follows [10]:

1) Identify all the extrema of $x(t)$. Initialize $d_0(t) = x(t)$.

2) Construct the upper envelope $e_u(t)$ and the lower envelope $e_l(t)$ by interpolating all the local maxima and minima via cubic splines, respectively.

3) Compute the average $m(t) = \left(e_u(t) + e_l(t)\right)/2$.

4) Extract the detail $d_1(t) = d_0(t) - m(t)$. If $d_1(t)$ satisfies the two above criteria (a and b) for an IMF, then $c_1(t) = d_1(t)$ becomes and IMF. Otherwise, return to the step 1 replacing $x(t)$ with $d_1(t)$.

5) The residue $r_1(t) = x(t) - c_1(t)$ is taken as the original data $x(t)$.

6) Repeat the steps 1-5 to obtain all possible IMFs.

The iterative process terminates when $r_1(t)$ is either a constant, or a monotonic slope or a function with only one extrema.

Finally, the original signal $x(\mathrm{t})$ is represented in terms of IMFs and the residue obtained with EMD method as:

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \qquad (1)$$

where N is the number of IMFs, $c_n(t)$ the nth IMF and $r_N(t)$ is the final residue. In this work, the algorithm proposed by Rilling et al. [13] for the implementation of the EMD was used. The two thresholds θ_1 and θ_2, and the tolerance parameter α, were set as 0.05, 0.05 and 0.05, respectively.

D. Frequency-based oscillatory components selection

For the LF components of each MMGdi signal, EMD method was calculated for a 20-sec segment, stepped in increments of 10-sec. The EMD can present some drawbacks during its execution such as the end effects [13]. To reduce distortion at the start and the end, a 10-sec centered window was analyzed on the 20-sec segment. Three steps were subsequently applied. First, for each IMF, the power spectral density (PSD) was estimated through the periodogram method (Hamming window) and the maximum frequency (f_{max}) corresponding to the highest value of PSD was calculated. Then, IMFs were chosen and summed, if their corresponding f_{max} values were in the range from 0.1 to 0.7 Hz to obtain a new segment based on oscillatory components. Second, the new segment was low-pass filtered using a zero-phase fourth- order, elliptic filter with a pass-band ripple of 0.3dB, and 50dB of attenuation in stop-band. The cut frequency of the filter was set as $1.15f_{max}$ of PSD. Third, the whole signal was low-pass filtered using a zero-phase fourth-order, Butterworth filter with a cut-off frequency of 1 Hz.

E. Data analysis

To evaluate the performance of the proposed method, the automated measurement of RR from IP signal and MMGdi signals were estimated and compared each 30-sec. RR from IP signal (RR_P) was obtained by taking all its maxima and then calculating the average of the difference between them. RR from MMGdi signals (RR_{MMG}) was calculated first combining left and right MMGdi components and then, calculating the maximum frequency of the spectrum. A

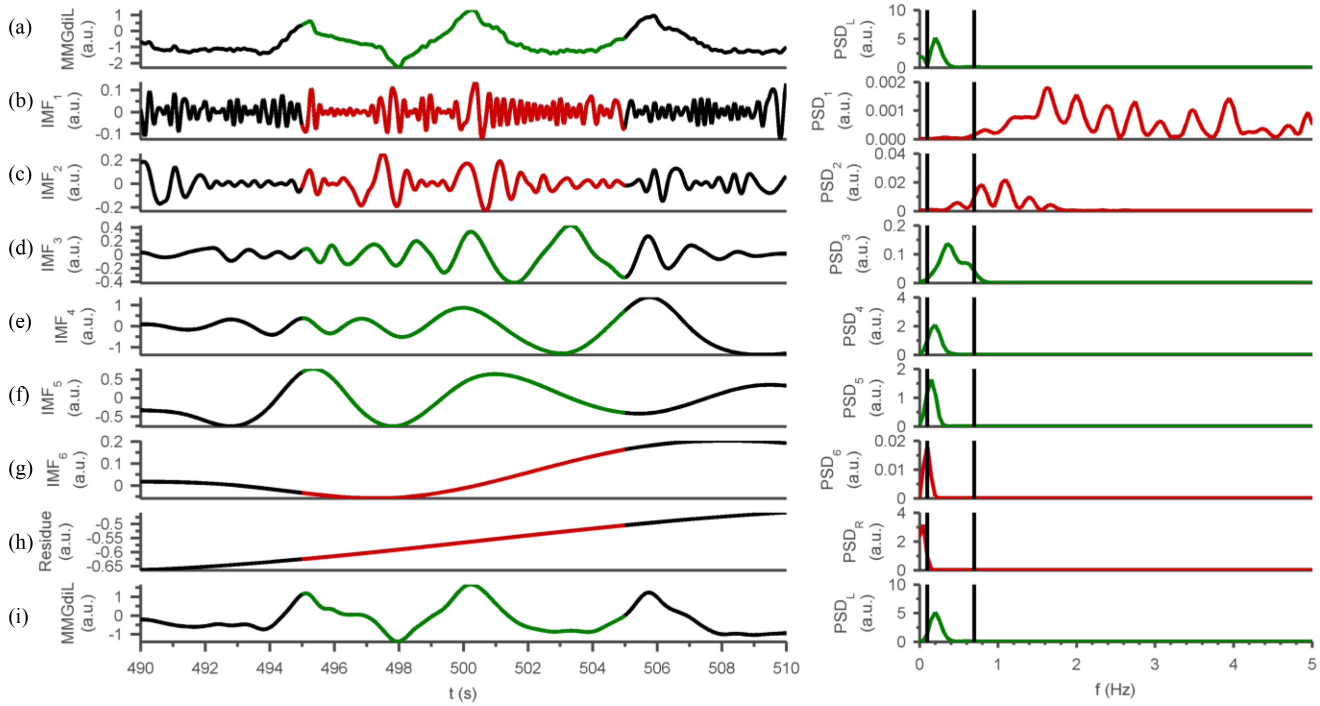

Figure 1. Left panel: (a) A 10 s segment of LF component from left hemidiaphragm, (b-h) six IMFs and a residue from the application of EMD and (i) the reconstruction of signal from the chosen IMFs. Right panel: PSD of the signal and the oscillatory components from EMD. An IMF was chosen in the case that f_{max} from PSD was in the range from 0.1 to 0.7 Hz (green color), otherwise the IMF was rejected (red color). The signal LF component of the signal was reconstructed by summing the chosen IMFs.

segment was discarded if, through visual inspection, it was corrupted by movement, cough or related artifacts.

The degree of association between the mean of RR_P and RR_{MMG} values was calculated by Pearson's correlation coefficient. Moreover, the agreement between the two measurements was carried out by a Bland-Altman plot. The mean bias was calculated as the average of the difference between the mean RR_P and RR_{MMG} values, while the limit of agreement, the interval within which 95% of the differences between measurements by the two methods are expected to lie, was based on the mean difference ± 2 times the standard deviation of the difference. All computations were performed with MATLAB (v. R2011b, Natick, Massachusetts, USA).

III. Results

Fig. 1 shows 20-sec of (a) the LF component MMGdi activity from left hemidiaphragm, (b-h) the application of EMD method and (i) the reconstruction of signal using the chosen IMFs (green color) and their corresponding spectrums. It is noted that a total of 6 IMFs and the residue were found to this segment of signal. The first components contain the higher oscillatory modes of the LF component (a wider spectrum) while the latter contain lower oscillatory modes (lower spectrum) and are more related to the respiratory movement. IMF components where chosen if the peak frequency of the spectrum was found in the range between 0.1 and 0.7 Hz. Fig. 2 depicts a 50-sec of simultaneous recording of (a) IP signal and both (b) left and (c) right LF components (red lines) during the incremental inspiratory load protocol. Also, raw mechanical activity (grey signals) was shown to note the waveforms and respiratory signal, which can difficult the proper evaluation respiratory movement. RR estimation was obtained from IP signal and the sum of left and right LF components obtained with EMD method. Fig. 3 illustrates the trend of the mean RR obtained by IP and the LF component during the inspiratory loading test for the healthy subject (~ 21 min of duration). It can be seen that both approaches were similar and exhibited a tendency to decrease and increases at the end, possible due to the distress of the test. On the other hand, the relationship between the mean RR_P and RR_{LF} values (Fig. 4a) was closer to the line of equality and shown a very strong linear association according to the Pearson correlation coefficient ($r = 0.86$). The Bland-Altman plot (Fig 4b) revealed a good agreement between the mean RR_P and RR_{MMG} values. It showed a mean difference (bias) of -0.21 breaths per minute (bpm) with a lower and an upper limit of agreement of -2.33 and 1.89 bpm, respectively.

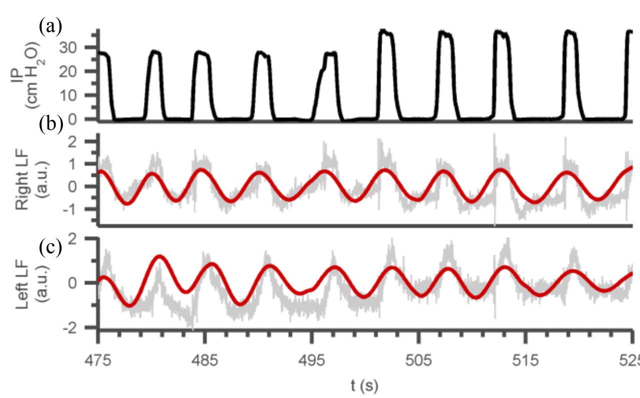

Figure 2. An excerpt of 50-sec of (a) IP signal, (b) left and (c) right mechanical hemidiaphragm activity during the incremental inspiratory load protocol. Grey signals represent the raw mechanical activity and red signals resultant LF component from MMGdi signals.

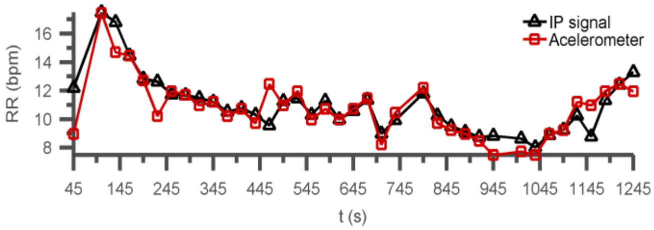

Figure 3. Trend of the mean RR_P and RR_{LF} values during the inspiratory loading test. bpm: breaths per minute.

IV. DISCUSSION AND CONCLUSION

This study aimed at evaluating the LF component of MMGdi signals in a healthy subject performing an inspiratory loading test, to extract respiratory movement from this mechanical activity. EMD method in conjunction with the use of classical filtering was applied to signals, acquired by means of a pair of capacitive accelerometers located at both sides of the rib cage. EMD is an adaptive method developed to analysis of non-linear and non-stationary time-series which decomposes it in IMFs. In [11] was observed that HF components of MMGdi signals were found in the first IMFs while the last IMFs reflected the respiratory movement. As expected, the collected signals are contaminated by different sources of noise [6], movement artifact [7], and waveforms [8] which difficult visual and automated tasks. Most of the relevant studies in literature calculates the peak of the spectrum of a signal based on band-pass filtering adjusted by a set of rules [9], smoothing and detrending the signals [5] or using a series of selective filtering bank [7] to obtain LF component. In this work, left and right mechanical activity was combined to obtain the contribution of both sides. However, it could be possible to choose only one side for RR evaluation. Overall, our results have shown a strong correlation (r = 0.86) according to the Pearson's correlation coefficient. Furthermore, a good agreement was obtained by Bland-Altman with a bias of -0.21 bpm and limits of agreement -2.33 and 1.89 bpm. These results agree with a recent study conducted by Lapi et al, in which they preliminarily have reported that body size or thoracic deformities do not affect the measure of RR [4]. Finally, the proposed method can be more restrictive by not only use the f_{max} in the selection of IMF, but also taking into account the mean and median frequency from PSD.

In summary, this study highlights that RR can be estimated using capacitive accelerometers and EMD for extracting the respiratory movement from diaphragm mechanical activity. Therefore, the proposed technique could be a complementary tool for estimation of RR, acquiring respiratory movement in clinical applications. The results of this study need to be confirmed in a large number of subjects and tested in different scenarios.

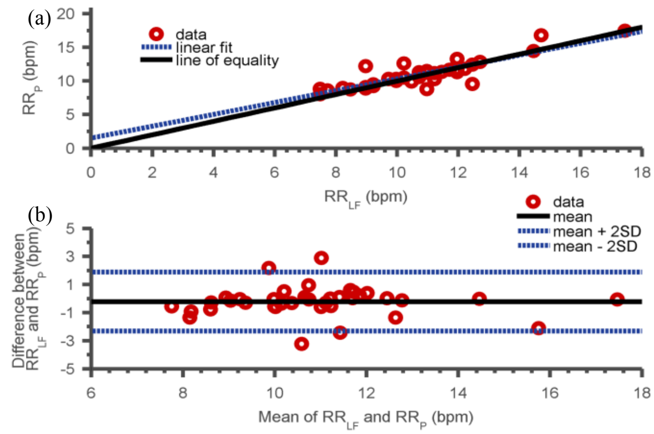

Figure 4. (a) Degree of association and (b) Bland-Altman plot for agreement between the mean RR_P and RR_{LF} values. bpm: breaths per minute, SD: standard deviation.

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