Analysis of respiratory mechanomyographic signals by means of the empirical mode decomposition

A Torres, R Jané, J A Fiz, E Lacier, J B Gálldiz, J Gea, J Morera

1 Biomedical Signals and Systems Division, Biomedical Engineering Research Centre (CREB), Universitat Politècnica de Catalunya (UPC), Pau Gargallo 5, 08024, Barcelona, Spain
2 Department of Pneumologie, Germans Trias i Pujol Hospital, Badalona, Spain
3 Gabinete de Tecnología Médica, Universidad Nacional de San Juan, San Juan, Argentina
4 Department of Pneumologie, Cruces Hospital, Baracaldo, Spain
5 Department of Pneumologie, Hospital del Mar, Barcelona, Spain

E-mail: abel.torres@upc.edu

Abstract. The study of the mechanomyographic (MMG) signals of respiratory muscles is a promising technique in order to evaluate the respiratory muscles effort. A critical point in MMG studies is the selection of the cut-off frequency in order to separate the low frequency (LF) component (basically due to gross movement of the muscle or of the body) and the high frequency (HF) component (related with the vibration of the muscle fibres during contraction). In this study, we propose to use the Empirical Mode Decomposition method in order to analyze the Intrinsic Mode Functions of MMG signals of the diaphragm muscle, acquired by means of a capacitive accelerometer applied on the costal wall. The method was tested on an animal model, with two incremental respiratory protocols performed by two non anesthetized mongrel dogs. The proposed EMD based method seems to be a useful tool to eliminate the low frequency component of MMG signals. The obtained correlation coefficients between respiratory and MMG parameters were higher than the ones obtained with a Wavelet multiresolution decomposition method utilized in a previous work.

1. Introduction
During muscular contraction, besides shortening and/or force produced, a transversal movement (perpendicular to muscle fibres direction) takes place. This movement is produced by lateral expansion of the activated muscle fibres and can be decomposed into two parts, according to the movement type: (1) a low frequency movement that takes place mainly during the beginning and the end of muscle contraction in isometric contractions, and in general during the whole contraction in dynamic contractions (LF component), (2) a high frequency movement that consists on small oscillations or vibrations that take place during the whole contraction (HF component). This second kind of movement is usually denominated mechanomyogram [1]. Both movements could be acquired by means of different non invasive sensors (air coupled microphones, piezoelectric contact sensors and accelerometers) fixed on the surface of the skin, over

---

6 To whom any correspondence should be addressed.
the muscle belly. It has been observed that the amplitude of both LF contraction components [2,3,4,5] and HF contraction components [1,6,7,8] of the muscular movement increase with the contraction force. The rationale for inferring the contraction muscle force, from the amplitude of the LF and HF components of the muscle movement, is that the signal constitutes the summation of muscle fibres movement from the recruited muscle motor units and their firing rate.

In previous works [9, 10, 11,12,13], our group has analysed the signal acquired by means of a capacitive accelerometer placed on the costal wall of the thoracic cage in order to register the mechanomyographic (MMG) signal of the diaphragm muscle. The LF component of this signal (mainly between 0 and 5 Hz) is supposed that is essentially due to the movement of the thoracic cage (produced by the contraction of all the respiratory muscles). The HF component (mainly between 2 Hz and 40 Hz) could have components of vibration of the diaphragm that could be suitable for inferring the respiratory muscles activation, in general, and the diaphragm muscle activation, in particular.

In [12] a Wavelet decomposition method was presented in order to create a criterion to separate the HF and LF components, concluding that in each respiratory test it should be selected a different cut-off frequency to separate this two components. The main drawback of Wavelet (or Fourier) decomposition techniques is that the basis functions are fixed, and they do not necessarily match varying nature of MMG signals. Given that the MMG signals are stochastic and nonstationary, the purpose of this study was to analyse the behaviour of a decomposition technique more appropriate for this kind of vibratory signals: the Empirical Mode Decomposition (EMD) [14,15].

The EMD adaptively decomposes the signal into oscillating components or Intrinsic Mode Functions (IMFs). The EMD is in fact a type of filter bank decomposition method whose sub bands are built as needed to separate the different natural components of the signal. The EMD has been applied to a number of biomedical signals [16,17,18], motivating us to develop a method for MMG denoising, based on the EMD.

Therefore, the outline of the present paper is to introduce the EMD technique to decompose vibratory MMG signals in order to remove respiration and other low frequency artefacts and to relate the resulting high frequency component with the force developed by the respiratory muscles, evaluated by means of the inspiratory pressure.

2. Methodology

2.1. Signal Acquisition

Two tracheostomized mongrel dogs (15-20 kg) were instrumented in order to acquire the diaphragmatic MMG signal and the inspiratory pressure. The diaphragmatic MMG signal was acquired with a Kistler 8302A capacitive accelerometer placed on the surface of the thoracic cage. The placement of the sensors (between the seventh and eighth intercostal spaces in the anterior axillary line) was chosen with the intention of obtaining the mechanomyographic signal of the diaphragm muscle. Inspiratory pressure (Pins) was measured with a pressure transducer placed in the trachea. Animals were awake, and on all fours position during the study. The two dogs performed an inspiratory progressive resistive load respiratory test.

All analog signals were amplified (HP 8802A), analog filtered, digitized with a 12 bit A/D system at a sampling rate of 4 kHz, and decimated at a new sampling rate of 100 Hz. Figure 1 shows an example the Pins and diaphragmatic MMG signal corresponding to sixteen respiratory cycles with increasing level of respiratory effort.
The duration and number of cycles of the respiratory tests performed are shown in table 1.

|     | No. cycles | Duration (s) |
|-----|------------|--------------|
| P1  | 88         | 322          |
| P2  | 83         | 332          |

**Table 1.** Cycles and duration of the respiratory tests.

![Figure 1](image.png)

**Figure 1.** Example of (a) the inspiratory pressure signal and (b) the diaphragmatic mechanomyographic (MMG) signal corresponding to sixteen respiratory cycles with increasing level of respiratory effort.
2.2. Empirical Mode Decomposition

The Empirical Mode Decomposition (EMD) [14] is a general nonlinear non-stationary signal decomposition method. The aim of the EMD is to decompose the signal into a sum of Intrinsic Mode Functions (IMFs). An IMF is defined as a function that satisfies two conditions: (1) the number of extrema and the number of zero crossings must be either equal or differ at most by one, and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero (or close to zero).

The major advantage of the EMD is that the IMFs are derived directly from the signal itself and does not require any a priori known basis. Hence the analysis is adaptive, in contrast to Fourier or Wavelet analysis, where the signal is decomposed in a linear combination of predefined basis functions.

Given a signal \( x(t) \), the algorithm of the EMD can be summarized as follows [14]:

1. local maxima and minima of \( d_0(t) = x(t) \).
2. Interpolate between the maxima and minima in order to obtain the upper and lower envelopes \( e_u(t) \) and \( e_l(t) \), respectively.
3. Compute the mean of the envelopes \( m(t) = (e_u(t) + e_l(t))/2 \).
4. Extract the detail \( d_1(t) = d_0(t) - m(t) \).
5. Iterate steps 1-4 on the residual until the detail signal \( d_k(t) \) can be considered an IMF (accomplish the two conditions): \( c_1(t) = d_1(t) \).
6. Iterate steps 1-5 on the residual \( r_n(t) = x(t) - c_n(t) \) in order to obtain all the IMFs \( c_1(t), ..., c_N(t) \) of the signal.

The procedure terminates when the residual \( c_N(t) \) is either a constant, a monotonic slope, or a function with only one extrema.

The result of the EMD process produces \( N \) IMFs \( (c_1(t), ..., c_N(t)) \) and a residue signal \( (r_N(t)) \):

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

The lower order IMFs capture fast oscillation modes of the signal, while the higher order IMFs capture the slow oscillation modes.

The main inconvenient of the EMD is that the technique is essentially defined by an algorithm and there is not an analytical formulation to obtain the IMFs. Furthermore, several algorithmic variations have been proposed in order to obtain the IMFs decomposition. In this paper we have used the algorithm proposed in [15,19], in which, in order to accomplish the second IMF condition, it is utilized a criterion that compares the amplitude of the mean of the upper and lower envelopes with the amplitude of the corresponding IMF. This criterion is based on two thresholds (\( \theta_1 \) and \( \theta_2 \)) and a tolerance parameter (\( \alpha \)). In this work we have used the default values proposed in [15]: \( \alpha = 0.05 \), \( \theta_1 = 0.05 \) and \( \theta_2 = 0.5 \).

Figure 2 shows an example of the first five IMF obtained with the described EMD decomposition method applied on a real respiratory MMG signal.
Figure 2. Empirical Mode Decomposition (EMD) of an example of sixteen respiratory cycles of a diaphragmatic MMG signal. (a1-g1) time signals (a2-g2) power spectral density estimation of the signals.

2.3. Data Analysis
Identification of respiratory cycles and detection of initial and final time of diaphragm muscle contraction was made by means of the inspiratory pressure (P_{ins}) signal. Two P_{ins} signal parameters were estimated: the mean (P_{m}) and maximum (P_{M}) inspiratory pressure achieved during the respiratory cycle. Two parameters were also estimated in every decomposition component of the MMG signal: the root mean square (RMS) and the Shannon entropy (H). The Shannon entropy is a measure that is based on the probability density function p(x) of the signal, and therefore represents the statistical changes and variations of the signal. The probability density function of the MMG signal is wider in contractions with high respiratory efforts than in contractions with low respiratory efforts. Thus, the entropy in contractions with a high inspiratory pressure level is greater than that in contractions with a low inspiratory pressure level. Given a system A with \( N \) possible states \( \{a_1, a_2, ..., a_N\} \) each one with its corresponding probability \( p(a_i) \), the Shannon entropy of the system \( H \) is defined as the average amount of information gained from a measurement that specifies one particular value \( a_i \)

\[
H = - \sum_{i=1}^{N} p(a_i) \log p(a_i)
\]

For equiprobable events the entropy is maximal (\( H_{\text{max}} = \log(N) \)), and if the probability of one event \( a_i \) is one and all the other probabilities are zero, the entropy is minimal (\( H_{\text{min}} = 0 \)). The Shannon entropy remains unchanged when adding events with zero probability.

The relationship between the P_{ins} and MMG parameters were analyzed by means the Pearson correlation coefficient.
3. Results
Figure 2 shows an example of the EMD decomposition method applied on a real respiratory MMG signal. Each IMF component represents a different part of the MMG signal, giving a breakdown of different causation parts of the total composite MMG signal. The EMD method yields five IMF components and a residue. As it could be seen in the spectrum of the signals, the lower order IMFs capture fast oscillation modes of the signal, while the higher order IMFs capture the slow oscillation modes. The first three IMFs are highly related with the vibratory activity of the diaphragm muscle, whereas the IMF5 and the residue are more related with the low frequency movement of the thoracic cage produced during respiration. Then, the vibratory activity of the diaphragm can be reconstructed as the sum of the first three IMFs.

Correlation between Pm parameters (PM and Pm) and parameters of the diaphragmatic MMG parameters (H and RMS) are shown in Table 2. In general, the correlation coefficients of the lower order IMFs are higher than the higher order ones. Also, as it was concluded in [13], the correlation coefficients obtained with the entropy parameter (H) are higher than the ones obtained with the RMS.

| IMF   | Pm RMS | Pm H  | PM RMS | PM H  |
|-------|--------|-------|--------|-------|
| IMF1  | 0.60   | 0.63  | 0.75   | 0.69  |
| IMF2  | 0.44   | 0.68  | 0.67   | 0.63  |
| IMF3  | 0.17   | 0.43  | 0.67   | 0.63  |
| IMF4  | 0.07   | 0.43  | 0.68   | 0.64  |
| IMF5  | 0.28   | 0.47  | 0.60   | 0.54  |
| Residue| 0.21   | 0.20  | 0.16   | 0.12  |
| Sum1,2,3| 0.54   | 0.65  | 0.73   | 0.70  |

4. Discussion and Conclusions
This paper introduced EMD method as a novel tool for analysis of MMG signals. The study of MMG signals acquired during dynamic contractions has the dilemma of separation of the LF and HF components. The EMD method has the advantage that automatically estimates the vibratory components of the MMG signal in the first two-three components of the EMD decomposition, and these components are highly related with the force developed by the respiratory muscles. Furthermore, the EMD method could probably identify other types of vibration or movements (besides of respiratory muscles vibration, or respiratory movement) that could be acquired by the accelerometer utilized to acquire the MMG signal, and could not be related with the respiratory activity. Nevertheless, this supposition should be validated with further experiments in which it can be caused the appearance of this type of artefacts.

We concluded that the presented EMD method is an interesting technique to study the LF and HF components of MMG signals, because it takes into consideration the nonlinear and nonstationary nature of the MMG signals. Further investigation should be carried out to develop a more automatic criterion to interpret each IMF with its physiological meaning, but, in general, the HF vibratory activity of the muscle is concentrated in the lower IMFs while the respiratory movement LF component is concentrated in the higher IMFs of the EMD decomposition.
References

[1] C. Orizio, “Muscle Sound: bases for the introduction of a mechanomyogaphic signal in muscle studies,” Crit. Rev. Biomed. Eng., 21, pp. 201–243, 1993

[2] M. Petitjean, B. Maton, and J.-C. Cnockaert, “Evaluation of human dynamic contraction by phonomyography”, J. Appl. Physiol., 73, pp. 2567-2573, 1992

[3] D. B. Smith, T. J. Housh, G. O. Johnson, T. K. Evetovixh, K. T. Ebersole, and S. R. Perry, “Mechanomyographic and electromyogra-phic responses to eccentric and concentric isokinetic muscle actions of the biceps brachii”, Muscle & Nerve, 21, pp. 1438-1444, 1998

[4] J. Celichowski, K. Grottel, and E. Bichler, “Relationship between mechanomyogram signals and changes in force of human forefinger flexor muscles during voluntary contraction”, Eur. J. Appl. Physiol., 78, pp. 283-288, 1998

[5] C. Orizio, R. V. Baratta, B. He Zhou, M. Solomonow, and A. Veicsteinas, “Force and surface mechanomyogram frequency responses in cat gastrocnemious”, J. Biomech., 33, pp. 427-433, 2000

[6] M. J. Stokes and P. A. Dalton, “Acoustic myographic activity increases linearly up to maximal voluntary isometric force in the human quadriceps muscle,” J. Neurol. Sci., 101, pp.163–167, 1991.

[7] F. Esposito, D. Malgrati, A. Veicsteinas and C. Orizio, “Time and frequency domain analysis of electromyogram and soundmyogram in the elderly,” Eur. J. Appl. Physiol., 73, pp.503–510, 1996.

[8] G. O. Matheson, L. Maffey-Ward, M. Mooney, K. Laddy, K. Fung and Y. Zhang, “Vibromyography as a quantitative measure muscle force production,” Scand. J. Rehabil. Med., 29, pp.29–35, 1997.

[9] A. Torres, J.A. Fiz, J. Morera, A.E. Grassino,and R. Jané, “Non-Invasive Measurement of Diaphragmatic Contraction Time in Dogs,” 23th Ann. Conf. IEEE-EMBS, 2001.

[10] A. Torres, J.A. Fiz, J. Morera, A.E. Grassino,and R. Jané, “Time-Frequency representations of the diaphragmatic movement measured by a surface piezoelectric contact sensor in dogs,” 25th Ann. Conf. IEEE-EMBS, 2003.

[11] A. Torres, J.A. Fiz, B. Galdiz, J. Gea, and R. Jané, “Non invasive assessment of respiratory muscle effort by means the study of diaphragm movement registered with surface sensors. Animal model (dogs),” 26th Ann. Conf. IEEE-EMBS, 2004

[12] A. Torres, J.A. Fiz, B. Galdiz, J. Gea, J. Morera and R. Jané, “A Wavelet Multiscale Based Method to Separate the High and Low Frequency Components of Mechanomyographic Signals,” 27th Ann. Conf. IEEE-EMBS, 2005

[13] A. Torres, J.A. Fiz, B. Galdiz, J. Gea, J. Morera and R. Jané, “Inspiratory Pressure Evaluation by means of the Entropy of Respiratory Mechanomyographic Signals,” 28th Ann. Conf. IEEE-EMBS, 2006

[14] N. E.Huang, Z. Shen , S. R. Long, M. L. C. Wu, H. H. Shih, Q. N. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non stationary time series analysis,” Proceedings of the Royal Society of London Series A- Mathematical Physical and Engineerineering Sciences, vol. 454, no. 1971, pp. 903-995, Mar. 1998

[15] G. Rilling, P. Flandrin, and P. Gonçalvès, “On Empirical Mode Decomposition and its Algorithms,” IEEE-Eurasip Workshop on Nonlinear Signal and Image Processing NSIP-03, Grado (I) 2003.

[16] Yiyao Ye, J. Garcia-Casado, J.L. Martinez-deJuan, J.L. Guardiola and J.L. Ponce, “Identification of the Slow Wave of Bowel Myoelectrical Surface Recording by Empirical Mode Decomposition,” 28th Ann. Conf. IEEE-EMBS, 2006

[17] B. Weng, M. Blanco-Velasco, and K. E. Barner, “ECG Denoising Based on the Empirical Mode Decomposition,” 28th Ann. Conf. IEEE-EMBS, 2006
[18] E. Rocon, J.L. Pons, A.O. Andrade, and S.J. Nasuto, “Application of EMD as a novel technique for the study of tremor time series,” 28th Ann. Conf. IEEE-EMBS, 2006

[19] EMD Matlab 7.1 codes with examples: http://perso.ens-lyon.fr/patrick.flandrin/emd.html

Acknowledgments
This study was supported in part by a grant from Ministerio de Educación y Ciencia and FEDER (TEC2004-05263-C02-01), Spain.