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Inspiratory Pressure Evaluation by means of the Entropy of Respiratory Mechanomyographic Signals

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***Abstract*— The study of the mechanomyographic (MMG) signal of respiratory muscles is a promising technique in order to evaluate the respiratory muscles effort. The relationship between amplitude and power parameters of this signal with the respiratory effort performed during respiration is of great interest for researchers and physicians due to its diagnostic potentials. In this study, it was analyzed the MMG signal of the diaphragm muscle acquired by means of a capacitive accelerometer applied on the costal wall. The new methodology investigated was based in the calculation of the Shannon entropy of the MMG signal during the diaphragm muscle voluntary contraction. The method was tested in an animal model, with two incremental respiratory protocols performed by two non anesthetized mongrel dogs. The results obtained in the respiratory tests analyzed indicate that the Shannon entropy was superior to other amplitude parameter methods, obtaining higher correlation coefficients (with p-values lower than 0.001) with the mean and maximum inspiratory pressures. Furthermore in this study we have proposed a moving mode high pass filter in order to eliminate the very low frequency component recorded by the sensor and due to movement artifacts and the gross movement of the thorax during respiration. With this non linear filtering method we have obtained higher correlation coefficients (with both entropy and amplitude parameters) than with the Wavelet multiresolution technique proposed in a previous work.**

I. 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 also 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 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], our group has analyzed the signal acquired by means of a capacitive accelerometer placed on the costal wall of the thoracic cage in order to record the mechanomyographic (MMG) signal of the diaphragm muscle. The LF component of this signal is supposed that it is essentially due to the movement of the thoracic cage (produced by the contraction of all the respiratory muscles). The HF component 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 every respiratory test should be selected a different cut-off frequency in order to separate this two components. In this work a non linear 0.25 s moving mode method has been applied in order to eliminate the very low frequency component essentially due to the movement of the thoracic cage.

Furthermore, in previous works [11, 12], the relationship between the diaphragmatic MMG signal and the inspiratory pressure signal was investigated only with the root mean square (RMS) of the MMG signal. Given the fact that the MMG signals are stochastic and nonstationary, the purpose

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of this study was to analyse the behaviour of a parameter that represents more statistical properties of the vibratory signal: the Shannon entropy. 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.

Therefore, the objective of this study is to analyse the HF component of the diaphragmatic MMG signal, and to relate and compare amplitude and entropy parameters extracted from this component with the force developed by the respiratory muscles evaluated by means of the inspiratory pressure.

II. METHODOLOGY

A. 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 (P_{ins}) 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 (MMG: 200 Hz; P_{ins}: 100 Hz).

The duration and number of cycles of the respiratory tests performed are shown in Table I.

TABLE I
CYCLES AND DURATION OF RESPIRATORY TESTS

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

B. Estimation of the probability density function p(x)

The most straightforward and widely used method to estimate the probability density function *p(x)* of a discrete signal is the histogram based technique. However this technique provides a not very accurate estimate of the *p(x)*, especially when the number of samples is small. An alternative to the histogram is the kernel density estimation (KDE) method. The KDE improves the histogram estimate of the probability density *p(x)* in terms of (i) a better mean square error rate of convergence of the estimate to the underlying density, (ii) an insensitivity to the choice of origin, and (iii) the ability to specify more sophisticated window shapes than the rectangular window for frequency counting [a]. The KDE estimation of the *p(x)* is defined as

$$\hat{p}(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x - x_i}{h}\right)$$

where *K(x)* is the kernel function that is required to be a probability density ($K(x) \geq 0$ and $\int_{-\infty}^{\infty} K(x)dx = 1$), and the parameter h is the smoothing parameter or window width. When we don't have an a priori knowledge of the *p(x)* a Gaussian kernel is typically used

$$K(x) = (2\pi)^{-0.5} e^{-\frac{x^2}{2}}$$

The choice of the bandwidth h is crucial since if h is chosen to small the variance increases and the estimator becomes noisier, while if h is too large the resulting $\hat{p}(x)$ is too smoothed. When using the Gaussian kernel the optimum value of h is given by

$$h_{opt} = 1.06\sigma_x N^{-0.2}$$

where σ_x is the standard deviation of the data [13].

C. Shannon Entropy Method

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_{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 ($H_{min}=0$). The Shannon entropy remains unchanged when adding events with zero probability.

In signal processing the entropy has been used as a measure for evaluating changes in the probability density function *p(x)*. As it is shown in Fig. 1(d), the *p(x)* of the MMG signal is wider in contractions with high respiratory efforts and narrower in contractions with low respiratory efforts. Thus, the entropy in contractions with a high inspiratory pressure level is greater than in contractions with a low respiratory level.

D. Signal processing

Identification of respiratory cycles, and detection of initial and final time of diaphragm muscle contraction was made by means of the 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.

The MMG signal was first pre-procesed (high-pass filtered) with a 0.25 s moving mode (most frequent value) method that was applied in order to eliminate the very low frequency component, essentially due to the movement of the thoracic cage. This filter consists in, for every sample of the MMG signal, obtaining the estimate of the *p(x)* of the MMG signal over a window of 0.25 s centered in this sample, calculating the mode of the distribution (maximum of *p(x)*), and subtracting this mode value to the value of the MMG signal. Fig. 1 b) shows an example of the original diaphragmatic MMG signal (continuous line) and the low frequency component of the MMG signal (dotted line) obtained with the moving mode filter.

In every respiratory cycle the entropy (H) and the root mean square (RMS) were estimated.

The relationship between the maximum and mean P_{ins} developed and the H and RMS obtained in every respiratory cycle was analyzed by means of the Pearson correlation coefficient.

III. RESULTS

Examples of the P_{ins} signal and the diaphragmatic MMG signal during 5 respiratory cycles are shown in Fig. 1 a) and b), respectively. Fig. 1 c) shows the result of applying the 0.25 s moving mode high-pass filter over the MMG signal. As it can be seen, using this method the very low frequency component, essentially due to respiratory movement, is cancelled. Fig. 1 d) shows an example for the KDE estimator using three sequences of 600 samples (1.2 s) from MMG signals with high (s1), low respiratory effort (s3), and with absence of respiratory effort (s2). As it can be seen, the *p(x)* of the signal with high respiratory effort (s1) has higher standard deviation, and therefore, higher entropy, whereas the *p(x)* of the apnea signal (s2) is concentrated around zero, and therefore lower entropy.

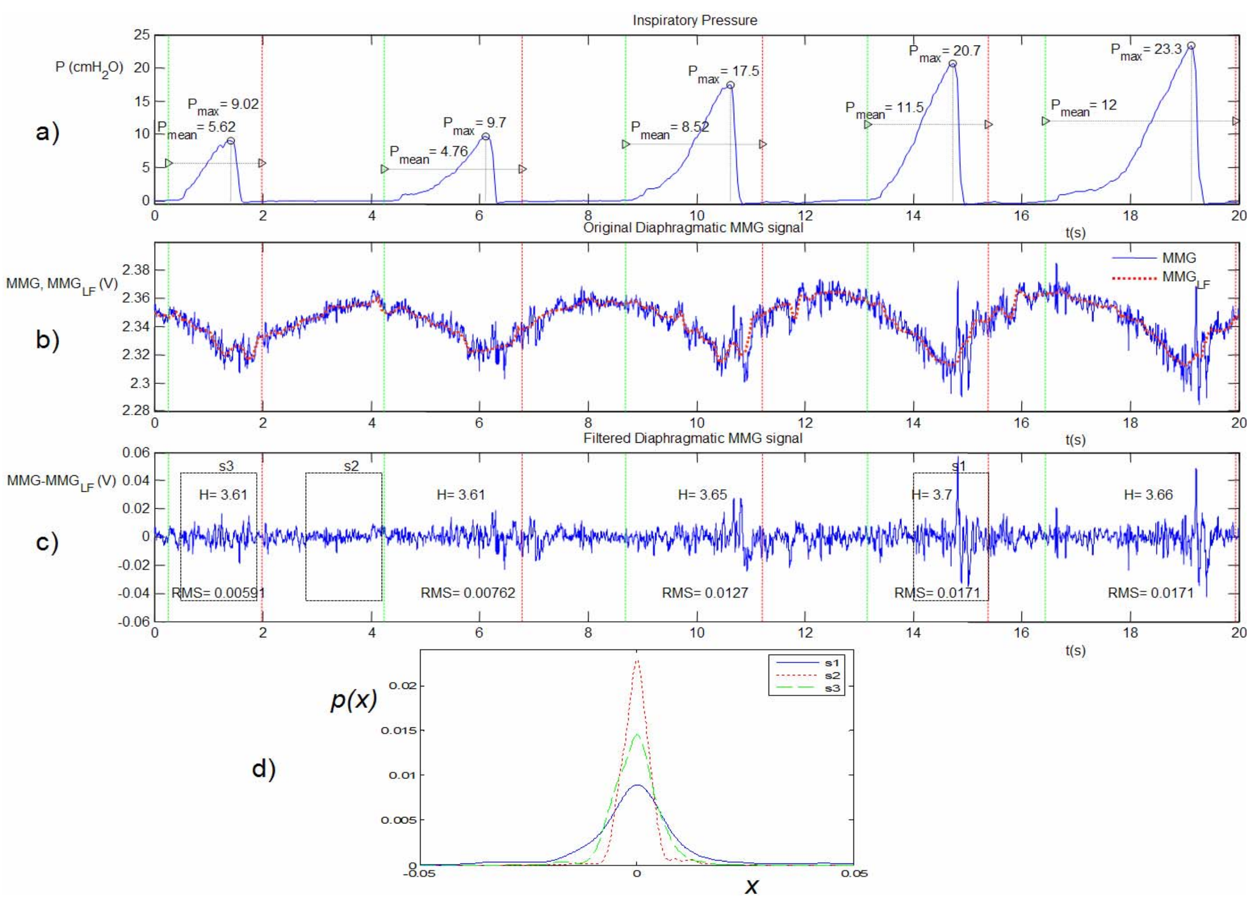

Fig. 1. (a) Example of 5 respiratory cycles of the inspiratory pressure signal, (b) diaphragmatic mechanomyographic (MMG) without high-pass filtering and a 0.25 s moving mode of the signal, (c) high-pass MMG filtered signal resulting from the subtraction of the mode to the original MMG signal, and (d) example for the kenrel density estimation method (KDE) of the probability density function of three different MMG segments.

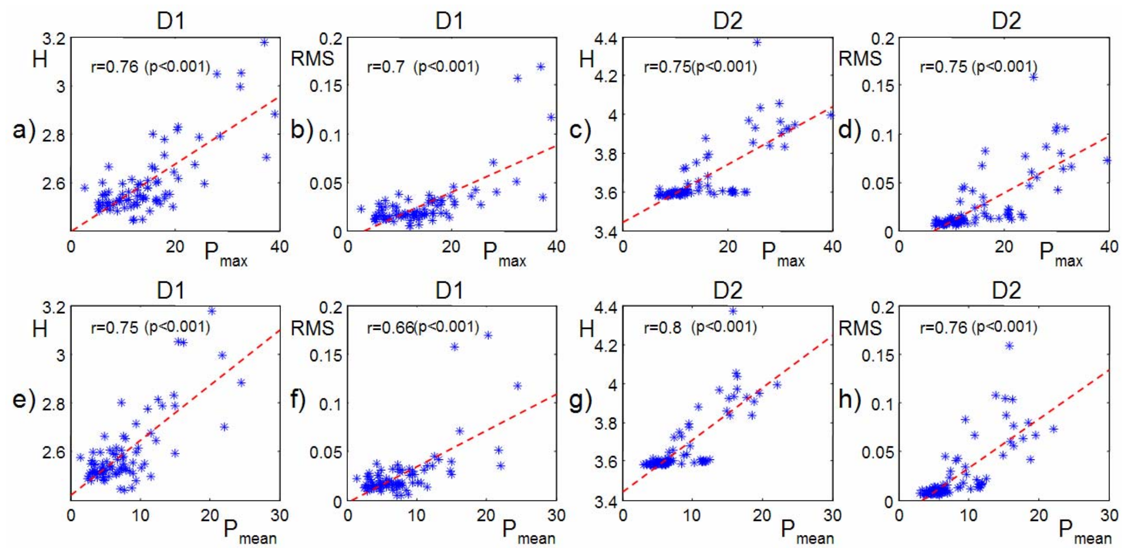

Fig. 2. Relationship and correlation coefficients between the inspiratory pressure parameters: Maximum pressure (Pmax) and mean pressure (Pmean), and parameters estimated with the diaphragmatic mechanomyographic signal: Shannon entropy (H) and root mean square (RMS).

Correlation coefficients (all the p-values were lower than 0.001) between P_{ins} parameters (P_M and P_m) and parameters of the diaphragmatic MMG parameters (H and RMS) are shown in Fig. 2 (P_M: a,b,c,d; P_m: e,f,g,h; H: a,c,e,g; RMS: b,d,f,h). It can be observed that the correlation coefficients obtained with the entropy parameter (H) are higher than the ones obtained with the RMS parameter.

IV. Discussion and Conclusions

In this work a Shannon entropy based method has been proposed in order to evaluate the changes in the diaphragmatic MMG signal with the intensity of respiratory muscles contraction effort, evaluated by means of the inspiratory pressure signal. In comparison with other methods based in amplitude or power parameters [11,12], the proposed method is superior in robustness to low frequency artefacts, providing higher correlation coefficients in all the respiratory tests and parameters analyzed.

Furthermore in this study we have solved the dilemma of the selection of the cut-off frequency of the high-pass filter needed in order to separate the LF and the HF component of the respiratory MMG [12], by means of the use of a moving mode filter. By means of the moving mode based low-pass filtering method the correlation coefficients between the inspiratory pressure parameters and the diaphragmatic MMG signal parameters have improved, regarding the results obtained in previous works [11,12].

We concluded that the presented entropy method is an interesting technique to study the behaviour of respiratory MMG signals during contraction. Further investigation should be carried out to develop calibration method that allows to estimate the respiratory effort by means of entropy parameters of the MMG signal.

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