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# Study of the Oscillatory Breathing Pattern in Elderly Patients

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***Abstract*— Some of the most common clinical problems in elderly patients are related to diseases of the cardiac and respiratory systems. Elderly patients often have altered breathing patterns, such as periodic breathing (PB) and Cheyne-Stokes respiration (CSR), which may coincide with chronic heart failure. In this study, we used the envelope of the respiratory flow signal to characterize respiratory patterns in elderly patients. To study different breathing patterns in the same patient, the signals were segmented into windows of 5 min. In oscillatory breathing patterns, frequency and time-frequency parameters that characterize the discriminant band were evaluated to identify periodic and non-periodic breathing (PB and nPB). In order to evaluate the accuracy of this characterization, we used a feature selection process, followed by linear discriminant analysis. 22 elderly patients (7 patients with PB and 15 with nPB pattern) were studied. The following classification problems were analyzed: patients with either PB (with and without apnea) or nPB patterns, and patients with CSR versus PB, CSR versus nPB and PB versus nPB patterns. The results showed 81.8% accuracy in the comparisons of nPB and PB patients, using the power of the modulation peak. For the segmented signal, the power of the modulation peak, the frequency variability and the interquartile ranges provided the best results with 84.8% accuracy, for classifying nPB and PB patients.**

## I. INTRODUCTION

As the elderly population continues to rise worldwide, the need for improved information and analysis of aging has increased. Knowledge is essential to assist in the definition of objectives and programs to care for elderly people, and social and political changes are required, among other factors. The Department of Economic and Social Affairs of the United Nations Secretariat has presented a detailed account of population dynamics, related to demographic development, changes in the balance of age groups and the socio-economic characteristics of the largest population, among others [1].

The commonest clinical problems in the elderly are related to diseases of the respiratory and cardiac systems. A recently report of British Society for Heart Failure [2] stated that heart failure is a highly prevalent condition, often with poor outcomes: an estimated 900,000 people in the U.K. have heart failure and over a third die within a year of diagnosis. However, clinical diagnosis can be problematic in elderly people, many of whom have extensive comorbidities that contribute to complicating their heart failure. Furthermore, good clinical management has been shown to substantially improve patient outcomes. Chronic heart failure (CHF) is a progressive disorder that not only affects the heart, but also other organs such as the lungs and the kidneys. Though CHF may be caused by different factors, other conditions can make it worse, and aging plays a considerable role in its risk. Several studies have presented relations between aging, heart failure and respiratory disease [3], [4], contrast with younger patients diagnosed with CHF [5].

Periodic breathing (PB) could be an indicator of the presence of CHF. CHF is associated with major abnormalities of autonomic cardiovascular control, and is characterized by enhanced sympathetic nerve activity and cardiorespiratory disarrangement. The PB pattern is characterized by rises and falls in ventilation, and can be classified into ventilation with apnea, known as CheyneStokes respiration (CSR), and ventilation without apnea [6]. PB has a prevalence as high as 70% in CHF patients [7], and is associated with increased mortality [8], especially in CSR patients [9]. Clinical studies show that elderly patients often have altered breathing pattern, with PB and CSR, coinciding simultaneously with the presence or absence of CHF [10].

Breathing patterns are also influenced by wakefulness or sleep, posture, and physiological and mental activity [11], [12]. Physiological parameters for the characterization and detection of different breathing patterns have been suggested in a number of clinical studies [13], [14]. In patients with mild to severe CHF, the power of cardiovascular oscillations in the very low frequency band has been reported to be considerably increased by the presence of PB, which may distort prognosis [15]. Often, the same patient may exhibit a continuum of different breathing patterns, ranging from normal breathing, without cyclic modulation of ventilation, to mild PB up to CSR pattern.

In our previous studies we worked with a database of CHF patients to identify and determine parameters for classifying patients with and without a PB pattern [16], [17]. In this study, we analyzed patients over 70 years admitted to short stay unit. Acute elderly patients may have associated pathology that is often complicated by the presence of multiple comorbidities. The main objective of this study is to extract relevant information from the respiratory pattern, which could then be used to discriminate patients with and without a PB pattern. In order to detect patterns of the respiratory oscillations, we obtain parameters from time-frequency characterization of the envelope of the respiratory flow signal. This respiratory pattern characterization might

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improve the automatic detection of PB and can be used to discriminate mildly symptomatic CHF patients from those at higher risk.

## II. Datasets

Respiratory flow signals were recorded from 25 elderly patients admitted in the short stay unit (13 males, 12 females, aged 81±6 years) at the Santa Creu i Sant Pau Hospital in Barcelona, Spain. All subjects were studied according to a protocol previously approved by the local ethics committee (Ref. IIBSP-VEN-2012-168). The respiratory flow signal was acquired using a pneumotachograph connected to a mask (Neumotachometer Fleisch F3 - Honeywell 176 PC).

Prior to data acquisition, patient were allowed to adapt for a few minutes so that they could feel comfortable with the mask. Respiratory flow signals were acquired for 15 min. All subjects were seated and remained awake throughout the acquisition.The signals were recorded at 250 Hz sampling rate.

The patients were classified into two groups according to clinical criteria: 7 patients with a periodic breathing pattern (PB) and 15 patients with a non-periodic breathing pattern. The remaining 3 patients were excluded from the study by problems with the records. Three of the patients with periodic breathing were classified as Cheyne-Stokes respiration (CSR) and 4 as without apnea (PB). The same patient might present a mixture of breathing pattern, ranging from normal breathing (with no cyclic modulation of ventilation) through mild PB to CSR patterns.

## III. Methodology

### A. Signal preprocessing

The respiratory flow signal was preprocessed to reduce artifacts. First, outlier samples below or above the threshold were removed. The threshold was taken as the mean of the signal $\pm 3$ standard deviation. Next, short-duration spikes were removed using an auxiliary filtered signal, obtained as the original flow signal downsampled to 25 Hz and filtered by a median filter of order 11. Thus, samples for which the difference between the downsampled original signal and the auxiliary signal exceed a threshold (set to half the standard deviation of the signal) were replaced by the median value of neighboring samples. Finally, considering that the respiratory frequency normally ranges from 0.2 to 0.4 Hz and the modulation frequency from 0.01 to 0.04 Hz, the signal was downsampled to 1 Hz. These frequency ranges are in good agreement with those previously reported by Pinna et al. [12]. Fig. 1 shows an example of the preprocessed respiratory flow signal for a patient from each group.

### B. Breathing pattern characterization

The respiratory pattern characterization was based on the envelope of the respiratory flow signal, using the Hilbert transform [18]. Due to the oscillatory character of envelope signal, the Welch method was used for the spectral analysis. The Welch method is based on the modified periodogram average. It allows for overlapping data segments and is given by

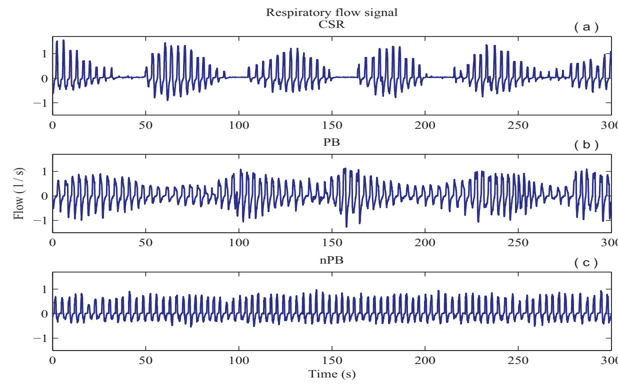


Fig. 1. Preprocessed respiratory flow signal of a patient with (a) a Cheyne-Stokes respiration pattern, (b) a periodic breathing pattern, and (c) a non-periodic breathing pattern.

$$\hat{P}_x^{(i)}(e^{j\omega}) = \frac{1}{D \cdot U} \left| \sum_{n=0}^{D-1} x_i(n) \cdot w(n) \cdot e^{-j\omega n} \right|^2, \quad i = 0, 1, \ldots, L-1 \tag{1}$$

where $D$ is the segment length, $x_i(n)$ is the data segment, and $w(n)$ is the temporal Hanning window. $U$ is the normalization factor for the power in the window function, which removes the energy bias introduced by the windowing. It is defined as

$$U = \frac{1}{D} \sum_{n=0}^{D-1} w(n)^2. \tag{2}$$

The Welch PSD is estimated by averaging these modified periodograms:

$$\hat{P}_{x\ Welch}(e^{j\omega}) = \frac{1}{L} \sum_{i=0}^{L-1} \hat{P}_x^{(i)}(e^{j\omega}). \tag{3}$$

To determine the envelope frequencies, we analyzed 700 s windows with an overlap of 50%. The time-frequency study was carried out using 300 s windows and an overlap of 95%. In order to study different breathing patterns in the same patient, the signals were segmented into windows of 5 min. All segments were processed independently, to classify the patients into a periodic or not periodic breathing pattern. The power spectral density (PSD) of time evolution was obtained using the Welch method with 300 s windows and an overlap of 50%.

### C. Parameter extraction

Table I and Fig. 2 present the parameters extracted from the envelope of the respiratory flow signal, in order to characterize the respiratory pattern of elderly patients.

The time-frequency evolution is analyzed through the mean and standard deviation of the parameters that characterize the breathing patterns.

### D. Data analysis

The accuracy of our pattern characterization was evaluated in terms of the following classification problems: patients with either PB (with and without apnea) or nPB patterns, and patients with CSR vs. PB, CSR vs. nPB and PB vs. nPB patterns. The statistical analysis was carried out using

TABLE I

PARAMETER DESCRIPTION

| Parameter | Units | Description |
|---|---|---|
| | | *Frequency parameters* |
| $f_c$ | Hz | Central frequency (power to 50%) |
| $f_a$ | Hz | Average frequency |
| $f_p$ | Hz | Frequency peak |
| $f_{SD}$ | Hz | Standard deviation of frequency peak |
| $HF/LF$ | Hz | Ratio between high and low frequency bands |
| $f_{Q1}$ | Hz | Frequency of the first quartile |
| $f_{Q3}$ | Hz | Frequency of the third quartile |
| $IQR$ | Hz | Interquartile frequency range |
| $f_{max}$ | Hz | Frequency over 95% of total power |
| $R$ | Hz | Frequency range defined as $R = \|f_p - f_a\|$ |
| | | *Amplitude parameters* |
| $A_{max}$ | $mV^2/Hz$ | Amplitude of $f_p$ |
| $P_w$ | $mV^2/Hz$ | Power band |

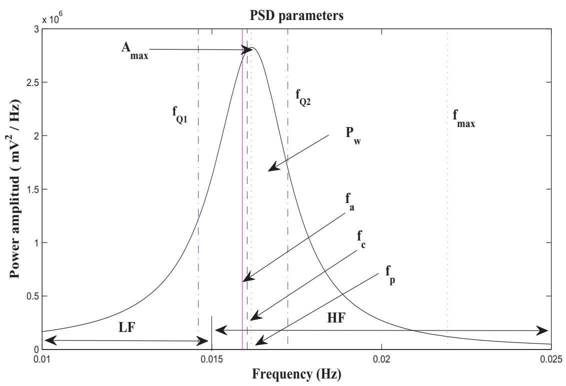


Fig. 2. Parameters extracted from the PSD of the envelope of the respiratory flow signal.

the SPSS program. The differences between the groups were tested by Kolmogorov-Smirnov and Mann-Whitney U tests. A $p$-value $< 0.05$ was considered significant. Using a linear classification procedure, a parameter selection process based on the leave-one-out cross-validation was employed to select the most discriminating parameters.

## IV. RESULTS

Figs. 3, 4 and 5 illustrate the performance of our method when it is applied to a patient with CSR, a patient with PB, and a patient with nPB breathing pattern, respectively. From Figs. 3 and 4, it is clear that the periodicity is also reflected in frequency domain through the modulation frequency peak. No obvious periodicity is observed in Fig. 5 with no clear modulation frequency peak and the reduction of the PSD.

Table II presents the statistically significant $p$-values of the most relevant parameters, obtained when the groups were compared. A comparison of PB and nPB patients only revealed differences in the parameters related to dispersion data. When nPB patients were compared to CSR patients, differences were obtained with parameters such as the frequency peak maximum amplitude and the power of the signal.

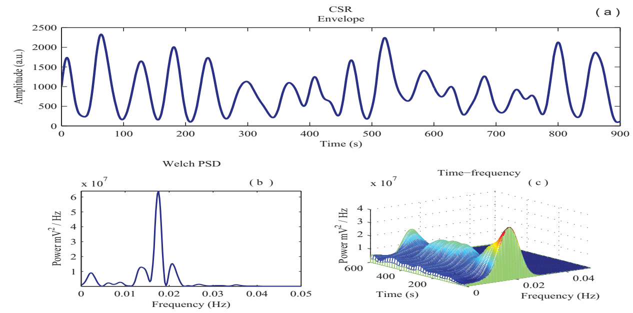


Fig. 3. (a) Envelope of the respiratory flow signal of a patient with CSR, (b) its PSD, and (c) its time-frequency evolution.

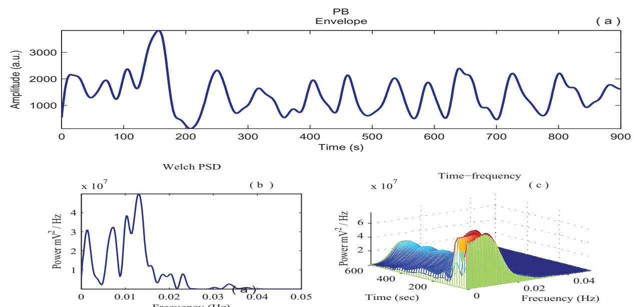


Fig. 4. (a) Envelope of the respiratory flow signal of a patient with PB, (b) its PSD, and (c) its time-frequency evolution.

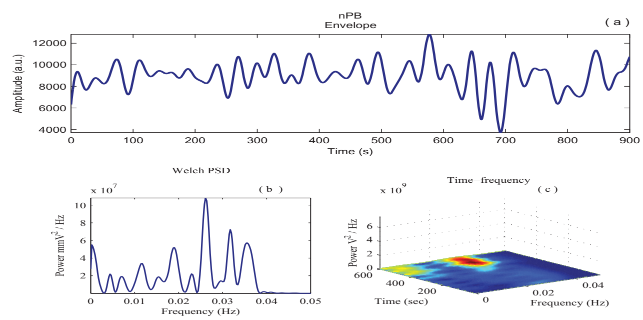


Fig. 5. (a) Envelope of the respiratory flow signal of a patient with nPB, (b) its PSD, and (c) its time-frequency evolution.

TABLE II

$p$-VALUE OF THE MOST SIGNIFICANT FREQUENCY PARAMETERS FOR EACH CLASSIFICATION, CALCULATED USING KOLMOGOROV-SMIRNOV TEST

| $p$-value | nPB vs. PB | nPB vs. CSR |
|---|---|---|
| $f_{SD}$ | 0.013 | – |
| $f_{Q1}$ | 0.047 | – |
| $IQR$ | 0.013 | |
| $A_{max}$ | – | 0.004 |
| $P_w$ | – | 0.004 |

Similar results were obtained when the mean and standard deviation of the evolution of frequency parameters were compared over time (Table III). When nPB and PB patients were compared, the most significant parameters were related to frequency variability. In contrast, the power-related parameters were the most significant for nPB vs. CSR patients.

TABLE III

$p$-VALUE OF THE MOST SIGNIFICANT PARAMETERS IN THE FREQUENCY EVOLUTION FOR EACH CLASSIFICATION, USING KOLMOGOROV-SMIRNOV TEST

| $p$-value | **nPB vs. PB** | **nPB vs. CSR** |
|---|---|---|
| Mean-$R$ | 0.013 | – |
| SD-$R$ | 0.013 | – |
| Mean-$f_{SD}$ | 0.013 | – |
| Mean-$A_{max}$ | – | 0.001 |
| SD-$A_{max}$ | – | 0.001 |

Table IV presents the most significant parameters obtained by studying the 5 min segments. Not only the significant difference was greater using segmented signal, but also PB compared by CSR patterns presented clear differences.

TABLE IV

$p$-VALUE OF THE MOST SIGNIFICANT PARAMETERS IN COMPARISONS OF 5 MIN SEGMENTS FOR THE THREE CLASSIFICATION GROUPS, USING MANN-WHITNEY U TEST

| $p$-value | **nPB vs. PB** | **nPB vs. CSR** | **PB vs. CSR** |
|---|---|---|---|
| $f_{SD}$ | 0.002 | $< 0.0005$ | – |
| $f_{max}$ | 0.004 | $< 0.0005$ | 0.033 |
| $IQR$ | 0.005 | 0.003 | – |
| $A_{max}$ | $< 0.0005$ | $< 0.0005$ | $< 0.0005$ |

Linear discriminant analysis was used to classify patients groups. $A_{max}$ was the most relevant parameter in comparisons of the mean and standard deviation of the evolution frequency. When the nPB and PB groups were compared, the accuracy was 81.8%. For 5 min segments, the best parameters were $f_{SD}$, $IQR$ and $A_{max}$, with an accuracy of 84.8% when nPB and PB were compared, and 80.3% in comparisons of all three groups.

## V. CONCLUSIONS

The characterization of the breathing pattern of elderly patients was analyzed through the envelope of the respiratory flow signal. Frequency and time-frequency methods were used to identify and classify patients into three groups, according to the periodicity of the respiratory flow signal. The power-related parameters allowed the best discrimination with the frequency method, while the frequency variability provided the best discrimination results between different groups of patients with the time-frequency method. The mean and the variability of the power modulation peak and its variance have providing an accuracy of 81.8% with 95.5% of well-classified patients between nPB and PB groups. For the segmented signal, the most discriminant parameters, the power of the modulation peak, the frequency variability and the interquartile ranges, provided an accuracy of 84.8% with 86.4% for patients well-classified into nPB and PB patterns. In classifications of nPB, PB and CSR patterns, an accuracy of 80.3% was obtained, 81.8% for well-classified patients. The proposed method suggest a useful tool for characterizing different respiratory patterns in elderly patients. The methods performance should be further evaluated on a larger set of flow signals.

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