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Characterization of the Respiratory Pattern Variability of Patients with Different Pressure Support Levels

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***Abstract*— One of the most challenging problems in intensive care is still the process of discontinuing mechanical ventilation, called weaning process. Both an unnecessary delay in the discontinuation process and a weaning trial that is undertaken too early are undesirable. In this study, we analyzed respiratory pattern variability using the respiratory volume signal of patients submitted to two different levels of pressure support ventilation (PSV), prior to withdrawal of the mechanical ventilation. In order to characterize the respiratory pattern, we analyzed the following time series: inspiratory time, expiratory time, breath duration, tidal volume, fractional inspiratory time, mean inspiratory flow and rapid shallow breathing. Several autoregressive modeling techniques were considered: autoregressive models (AR), autoregressive moving average models (ARMA), and autoregressive models with exogenous input (ARX). The following classification methods were used: logistic regression (LR), linear discriminant analysis (LDA) and support vector machines (SVM). 20 patients on weaning trials from mechanical ventilation were analyzed. The patients, submitted to two different levels of PSV, were classified as low PSV and high PSV. The variability of the respiratory patterns of these patients were analyzed. The most relevant parameters were extracted using the classifiers methods. The best results were obtained with the interquartile range and the final prediction errors of AR, ARMA and ARX models. An accuracy of 95% (93% sensitivity and 90% specificity) was obtained when the interquartile range of the expiratory time and the breath duration time series were used a LDA model. All classifiers showed a good compromise between sensitivity and specificity.**

I. INTRODUCTION

Mechanical ventilation is the principal medical treatment for acute respiratory failure and one of the most commonly used techniques in intensive care. Weaning is a process that usually involves the gradual removal of mechanical support to recover spontaneous breathing. McConville et al. recently presented an overview of strategies to reduce the duration of mechanical ventilation, and a list of risk factors for unsuccessful discontinuation of mechanical ventilation [1]. They showed that most patients who receive mechanical ventilation have acute respiratory failure in the postoperative period, pneumonia, congestive heart failure, sepsis, trauma, or acute respiratory distress syndrome. Spontaneous breathing trials assess a patients ability to breathe while receiving minimal or no respiratory support. However, both an unnecessary delay in the discontinuation process and a weaning trial that is undertaken too early are undesirable [2], [3].

Different studies have been performed to detect which physiological variables identify readiness to undertake a weaning trial [2], [3]. However, one of the most challenging problems in intensive care is still the process of discontinuing mechanical ventilation, as the percentage of patients who perform a successful trial but have to be reconnected to mechanical ventilation before 48 hours ranges from 6% to 47% [4] for different populations. A failed weaning trial is uncomfortable for the patient and may induce cardiopulmonary distress. Ventilator support should be withdrawn promptly when no longer necessary, to reduce the likelihood of known nosocomial complications and costs [5].

Spectral analysis is a tool that is widely used to assess many types of biomedical signals. Several studies have been carried out to estimate AutoRegressive (AR) and Moving Average (MA) models. Processes with spectral poles or narrow peaks are best described with AR models. MA models are suitable for processes with spectral zeros or narrow valleys using few parameters. AR models require many more parameters to approximate a spectrum with deep valleys. Finally, the combined ARMA models may be the optimal type for processes with a combination of spectral poles and zeros. Durbin used long AR models in MA estimation [6]. This method can produce accurate estimates if the order of the AR model is chosen correctly. Durbin's MA method is based on the theoretical and asymptotic equivalence of AR (∞) and MA (q) processes. In practice, estimates of finite order AR models must be used. A common choice has been to use the parameters of the best predicting AR model order, or an AR model order that depends on the number of MA parameters that are estimated [7], [8].

The quality of the selected model depends on the sample size used for the estimation, the number of observations, the estimation algorithm, and the order selection criterion. Several autoregressive estimation algorithms have been developed [9]. The asymptotic theory is more or less the same for all them. Many criteria exist for order selection, such as the final prediction error, asymptotic information criteria

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and the autoregressive transfer function criterion. Different variants of these criteria have been reported and studied. The penalty for estimating more parameters becomes a function of the sample size in the consistent method. A test for any model selection and estimation procedure is to apply it to the selection of a model class, and then analyze the results under the assumption that the data are generated by a model in one of the classes.

In our previous study, we used the respiratory flow signal to analyze the respiratory pattern of patients in the weaning process. We studied the variability of the respiratory time series and the pattern variability using autoregressive modeling techniques [10], [11]. In this study, we analyzed the respiratory pattern of the patients submitted to low and high pressure support (PSV), using the respiratory volume signal. We studied variability in the respiratory pattern using autoregressive models (AR), autoregressive moving average models (ARMA), and autoregressive models with exogenous input (ARX). The most relevant parameters were used to classify the patients. The aim of this study is to provide enhanced information of the respiratory pattern of patients submitted to different pressure support levels, on weaning trials process.

II. Methodology

A. Datasets

Respiratory volume signals were recorded from 20 patients on weaning trials from mechanical ventilation, in the Department of Intensive Care at the Santa Creu i Sant Pau Hospital in Barcelona, Spain. All subjects gave their informed consent and were studied according to a protocol previously approved by the local ethics committee. The respiratory volume signal was acquired by means of a non-invasive respiratory inductive plethysmograph. All subjects remained awake throughout the acquisition.

Patients were submitted to two levels of pressure support ventilation (PSV), classified as low PSV (5 ± 2 cmH_2O) and high PSV (12 ± 2 cmH_2O). Therefore, the database contains volume signals with different respiratory pattern variability. Respiratory volume signals were acquired for 30 min, recorded at 250 Hz sampling rate. Figure 1 illustrates an excerpt of respiratory volume signal from a patient.

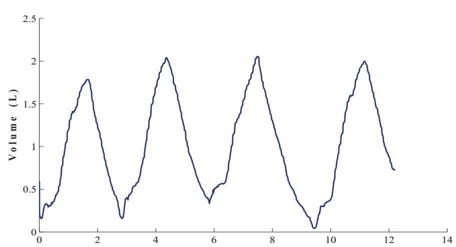

Fig. 1. Excerpt of respiratory volume signal from a patient.

The following time series were obtained from each recorded signal: inspiratory time (T_I), expiratory time (T_E), breath duration (T_{Tot}), tidal volume (V_T), fractional inspiratory time (T_I/T_{Tot}), mean inspiratory flow (V_T/T_I) and rapid shallow breathing (f/V_T), where f is the respiratory rate. For each time series mean (M), standard deviation (SD) and interquartile range (IQR) were obtained.

B. Modeling techniques

- *Autoregressive model (AR)*. The autoregressive (AR) model of order p can be written as AR(p), and is defined as

$$x(n) = a_1 x(n-1) + \cdots + a_p x(n-p) + e(n) \tag{1}$$

where $x(n)$ is the series under investigation, $a_1, ..., a_p$ are the autoregressive coefficients, and $e(n)$ is a zero-mean white noise with variance λ^2. The coefficients a_p and the variance λ^2 are estimated using the Levinson-Durbin recursion. The model order determination was based on the Akaike Final Prediction Error (FPE) [12], [13], defined as

$$FPE = s^2 p \frac{N+p+1}{N-p-1} \tag{2}$$

where p is the order of the model, N the number of data items and $s^2 p$ the total square error, which is given by

$$s^2 p = \frac{1}{N} \sum_{p}^{N-1} e^2(n). \tag{3}$$

- *Autoregressive moving-average model (ARMA)*. The power of ARMA models is that they can incorporate both autoregressive and moving average terms. The use of ARMA models was popularized by Box and Jenkins. The ARMA(p, q) model is given by

$$\begin{aligned} x(n) + a_1 x(n-1) + \cdots + a_p x(n-p) = \\ e(n) + b_1 e(n-1) + \cdots + b_q e(n-q) + \end{aligned} \tag{4}$$

where p and q are the orders of the process estimated by the Akaike criterion, and $a_1, ..., a_p$ and $b_1, ..., b_q$ are the coefficients of the model.

- *Autoregressive model with exogenous input (ARX)*. This model is defined with an exogenous input $u(n)$ and output $x(n)$, by

$$\begin{aligned} x(n) + a_1 x(n-1) + \cdots + a_p x(n-p) = \\ b_1 u(n-1) + \cdots + b_q u(n-q) + e(n) \end{aligned} \tag{5}$$

since p and q are the orders of the model, and $a_1, ..., a_p$ and $b_1, ..., b_q$ their coefficients [14]. The following parameters were calculated for each time series: model order, first coefficient of the model and final prediction error. The non-parametric Wilcoxon signed-rank test was used to compare the two groups.

C. Classification methods

Once the most relevant parameters had been obtained with the models presented above, the next classification methods were applied. The leave-one-out procedure was used to validate the results.

- *Logistic regression* is an approach to prediction, like ordinary least square regression. However, with logistic regression, research predicts a dichotomous outcome [15]. The model is given by

$$p = \frac{1}{1+e^{-(\alpha_0+\alpha_1 X_1+\alpha_2 X_2+\cdots+\alpha_i X_i)}} \tag{6}$$

where p is the occurrence probability of an event x of the data series X, and α_i is the weight of the parameters.

- *Linear discriminant analysis* can be used only for classification (i.e., with a categorical target variable), not for regression. The target variable may have two or more categories [16]. It has been defined as

$$Y = \mu_0 + \mu_1 X_1 + \cdots + \mu_k X_i \tag{7}$$

where X_i and μ_0 are the independent parameters and independent term, respectively, and μ_i are the discriminant function coefficients.

- *Support vector machines (SVM)* are based on transforming data into a higher dimensional space since they may convert a complex classification problem into a simpler one that can be solved by a linear discriminant function, known as a hyperplane, defined by [16]

$$f(x) = wz + b = \sum_{i=1}^{L} \alpha_i y_i K(x_i, x_j) + b \tag{8}$$

where α_i and b are determined to solve a large-scale quadratic programming problem, for which efficient algorithms exist that guarantee global optimum values [17], [18]. The linear Kernel (K) was selected.

III. Results

Figure 2 illustrates the respiratory time series of low and high PSV. Table I shows the mean and standard deviation of the respiratory time series by comparing the breathing pattern in low and high PSV. The mean number of breaths in the low PSV was 774, whereas in the high PSV it was 569, from 30 minutes of records. The most relevant parameters were selected to compare the low and high PSV breathing patterns.

Table II presents the lists of parameters that showed a higher statistically significant difference with the functions used for sorting by means of linear discriminant analysis, logistic regression and SVM. All possible combinations of parameters were analyzed.

Table III presents the best values for accuracy (*Acc*), sensitivity (*Sn*) and specificity (*Sp*) obtained with the proposed classification methods.

The linear discriminant function (Eq. 9), combining IQR T_E (X_2) and T_{Tot} (X_9), presented the best classification rate (95%).

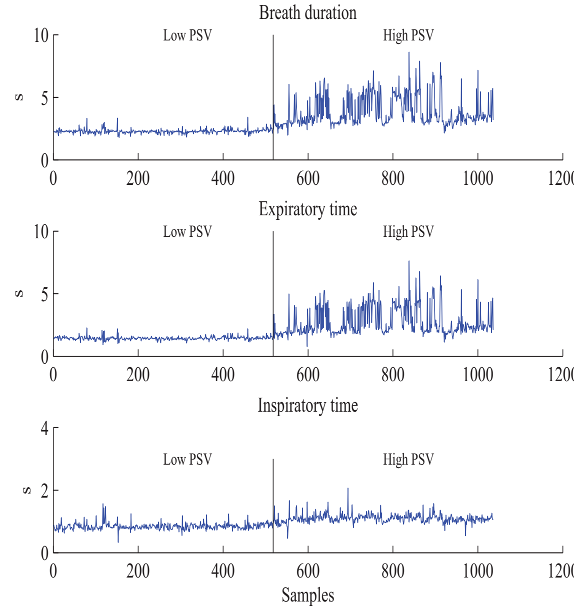

Fig. 2. Time series plots of breath duration (T_{Tot}), expiratory time (T_E) and inspiratory time (T_I) for two different levels of pressure support ventilation (PSV).

TABLE I

Mean(x), SD(x) and IQR(x) of time series when comparing low PSV and high PSV

	Low PSV	*High PSV*	*p-value*
M_T_I (s)	0.88 ± 0.12	1.05 ± 0.29	0.011
SD_T_I (s)	0.19 ± 0.15	0.24 ± 0.17	0.050
IQR_T_I (s)	0.14 ± 0.07	0.20 ± 0.14	0.026
M_T_E (s)	1.60 ± 0.59	2.59 ± 0.84	0.0001
SD_T_E (s)	0.74 ± 0.44	1.17 ± 0.81	0.002
IQR_T_E (s)	0.34 ± 0.37	$.99 \pm 0.78$	0.0001
M_T_{Tot} (s)	2.48 ± 0.65	3.63 ± 0.80	0.0002
SD_T_{Tot} (s)	0.34 ± 0.16	1.49 ± 0.64	0.005
IQR_T_{Tot} (s)	0.29 ± 0.13	1.22 ± 0.71	0.0001
M_T_I/T_{Tot}	0.38 ± 0.06	0.31 ± 0.06	0.001
SD_T_I/T_{Tot}	0.058 ± 0.03	0.09 ± 0.03	0.015
IQR_T_I/T_{Tot}	0.06 ± 0.04	0.08 ± 0.05	0.011
M_V_T (ml)	467 ± 195	602 ± 266	0.005
SD_V_T (ml)	107 ± 52	128 ± 66	n.s.
IQR_V_T (ml)	89 ± 39	95 ± 35	n.s.
M_V_T/T_I	548 ± 226	597 ± 209	n.s.
SD_V_T/T_I	154 ± 86	161 ± 84	n.s.
IQR_V_T/T_I	131 ± 76	129 ± 77	n.s.
f (breaths/min)	26 ± 6	18 ± 6	0.0001

$$0 = 1.5586 - 5.1853X_2 + 3.1998X_9 \tag{9}$$

The best classification rate (93%) when using the logistic regression function (Eq. 10) was obtained with the same parameters IQR T_E (X_2) and T_{Tot} (X_9).

$$p = \frac{1}{1+e^{(40.1757-250.9031X_2+174.8104X_9)}} \tag{10}$$

TABLE III

RANKING FUNCTIONS PROPOSED FOR THE DISCRIMINATION BETWEEN THE LOW AND HIGH PSV USING LINEAR DISCRIMINANT (LDA) ANALYSIS, LOGISTIC REGRESSION (LR) AND THE SUPPORT VECTOR MACHINE (SVM), IN TERMS OF ACCURACY (ACC), SPECIFICITY (SP) AND SENSITIVITY (SN)

Parameters	*Acc*			*Sp*			*Sn*		
	LDA	*RL*	*SVM*	*LDA*	*RL*	*SVM*	*LDA*	*RL*	*SVM*
X_2, X_9	0.95	0.93	0.93	0.90	0.92	0.93	0.93	0.95	0.92
X_2, X_7, X_9	0.94	0.91	0.92	0.91	0.92	0.92	0.90	0.89	0.92
X_2, X_6, X_9	0.91	0.91	0.92	0.93	0.94	0.92	0.88	0.89	0.93
X_2, X_7, X_8,X_9	0.94	0.89	0.91	0.91	0.89	0.90	0.87	0.87	0.92
X_2, X_{11}	0.87	0.90	0.86	0.79	0.92	0.91	0.92	0.88	0.81
X_2, X_8	0.88	0.87	0.86	0.81	0.89	0.91	0.92	0.86	0.81
X_1, X_2, X_3, X_9	0.92	0.86	0.89	0.88	0.87	0.87	0.85	0.86	0.90
X_2, X_9	0.95	0.93	0.93	0.90	0.92	0.93	0.93	0.95	0.92
X_2, X_3,X_9	0.93	0.88	0.88	0.88	0.85	0.85	0.85	0.97	0.90
X_2, X_{10}	0.87	0.90	0.87	0.75	0.92	0.92	0.94	0.87	0.82
X_2, X_5	0.87	0.88	0.86	0.77	0.91	0.91	0.90	0.85	0.81

TABLE II

THE RELEVANT PARAMETERS THAT CHARACTERIZED THE BREATHING PATTERN FOR LOW AND HIGH PSV USING LINEAR DISCRIMINANT ANALYSIS, LOGISTIC REGRESSION, AND SVM CLASSIFIERS

Name	Parameters	Series	*p*-value
X_1	Mean	T_E	0.0002
X_2	IQR	T_E	0.0011
X_3	Mean	T_{Tot}	0.0002
X_4	Mean	V_T	0.036
X_5	AR model FPE	T_E	0.0007
X_6	AR model FPE	T_{Tot}	0.0016
X_7	ARMA model FPE	T_E	0.0009
X_8	ARX model FPE	T_E	0.0007
X_9	IQR	T_{Tot}	0.0012
X_{10}	ARMA model FPE	T_{Tot}	0.0015
X_{11}	ARX model FPE	T_{Tot}	0.0013

IV. CONCLUSIONS

The analysis of respiratory time series by autoregressive modeling techniques significantly improved the identification of low and high variability levels, in comparison with the time domain analysis. The interquartile range and the final prediction errors of AR, ARMA and ARX models were statistical significant parameters in comparisons of the time series. When the groups of signals were classified using logistic regression, linear discriminant analysis and support vector machines, the accuracy was above 95%, with the best relation between specificity (90%) and sensitivity (93%). It seems that the proposed methodology could allow the automatic classification of volume signals into high (HV) and low variability (LV) levels. As a preliminary study these results suggest that the most relevant parameters obtained in the characterization of the respiratory pattern, using autoregressive modeling techniques, offer a promising approach to evaluate differences between patients on weaning trials, in order to identify the optimal extubation moment. The significance of the results, though being promising, needs to be further established on a larger set.

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