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Performance of Respiratory Pattern Parameters in Classifiers for Predict Weaning Process

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Abstract— **Weaning trials process of patients in intensive care units is a complex clinical procedure. 153 patients under extubation process (T-tube test) were studied: 94 patients with successful trials (group S), 38 patients who failed to maintain spontaneous breathing and were reconnected (group F), and 21 patients with successful test but that had to be reintubated before 48 hours (group R). The respiratory pattern of each patient was characterized through the following time series: inspiratory time (T_I), expiratory time (T_E), breathing cycle duration (T_{Tot}), tidal volume (V_T), inspiratory fraction (T_I/T_{Tot}), half inspired flow (V_T/T_I), and rapid shallow index (f/V_T), where *f* is respiratory rate. Using techniques as autoregressive models (AR), autoregressive moving average models (ARMA) and autoregressive models with exogenous input (ARX), the most relevant parameters of the respiratory pattern were obtained. We proposed the evaluation of these parameters using classifiers as logistic regression (LR), linear discriminant analysis (LDA), support vector machines (SVM) and classification and regression tree (CART) to discriminate between patients from groups S, F and R. An accuracy of 93% (98% sensitivity and 82% specificity) has been obtained using CART classification.**

I. Introduction

One of the most challenging problems in intensive care is the process of discontinuing mechanical ventilation, termed weaning. Despite advances in mechanical ventilation and respiratory support, the science of determining if the patient is ready for extubation is still very imprecise [1].When mechanical ventilation is discontinued, up to 25% of patients have respiratory distress severe enough to require reinstitution of ventilator support. A failed weaning trial is discomforting for the patient, may induce cardiopulmonary distress and carries a higher mortality rate. The number of patients that have to be reintubated before 48 h but previously performed successful trials represents a percentage higher than 10% [2]. Hence the need for a more accurate prediction of the optimal disconnection time, which is extended to the whole weaning process [3], [4].

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Several studies have reported that approximately 40% of the intensive care unit patients need mechanical ventilation. Among them, 90% of patients can be disconnected of the ventilator in a few days. Patients, who needed reintubation required longer hospital stays and had greater mortality [5].

Many weaning criteria's like minute volume, maximum inspiratory pressure, tidal volume, rapid shallow breathing and CROP (compliance, resistance, oxygenation and pressure) clinical index have been defined to determine whether a patient is able to come off the ventilator. Most of these tests are sensitive but are not specific; hence even if a patient fails the above weaning criteria, they could still be weaned. It has been shown that all the evaluated indices are poor predictors of weaning outcome in a general intensive care unit population [6], [7].

The respiratory pattern describes the mechanical function of the pulmonary system, and it can be characterized by the following time series: inspiratory time (T_I), expiratory time (T_E), breathing cycle duration (T_{Tot}), tidal volume (V_T), inspiratory fraction (T_I/T_{Tot}), half inspired flow (V_T/T_I), and rapid shallow index (f/V_T), where *f* is respiratory rate. The analysis of the respiratory pattern variability has been studied using autoregressive models (AR), autoregressive moving average models (ARMA), and autoregressive models with exogenous input (ARX). The most relevant parameters are obtained in [8]. In this work, the performance of classifiers as logistic regression (LR), linear discriminant analysis (LDA), support vector machines (SVM), and classification and regression tree (CART) are studied to discriminate between patients from successful (groups S), failed (group F), and reintubated (group R) trials.

II. Methodology

A. Subjects

Respiratory flow signals were measured in 153 patients on weaning trials from mechanical ventilation (WEANDB database). These patients were recorded in the Departments of Intensive Care Medicine at Santa Creu i Sant Pau Hospital, Barcelona, Spain, and Getafe Hospital, Getafe, Spain, according to the protocols approved by the local ethic committees.

The patients were submitted under T-tube test, disconnected from the ventilator and maintained spontaneous breathing through an endotraqueal tube during 30 min. If the patients maintained the spontaneous breathing with normality they were extubated, if not, they were reconnected. When the patients still maintained the spontaneous breathing after 48 h, the weaning trial process was considered successful, if not, the patients were reintubated.

The patients were classified into three groups: group S, 94 patients (61 male, 33 female, aged 65±17 years) with successful weaning trials; group F, 38 patients (24 male, 14 female, aged 67±15 years) that failed to maintain spontaneous breathing; and group R, 21 patients (11 male, 10 female, aged 68±14 years) who had successful weaning trials, but required reintubation in less than 48 h.

B. Characterization of Breathing Pattern

Respiratory flow signal was acquired using a pneumotachograph (Datex-Ohmeda monitor with a Variable-Reluctance Transducer) connected to an endotracheal tube. The signals were recorded at 250 Hz sampling rate, during 30 min. The respiratory signal was processed to obtain the following time series, for each patient: T_I, T_E, T_{Tot}, V_T, T_I/T_{Tot}, V_T/T_I, respiratory rate (f) and f/V_T (Fig.1).

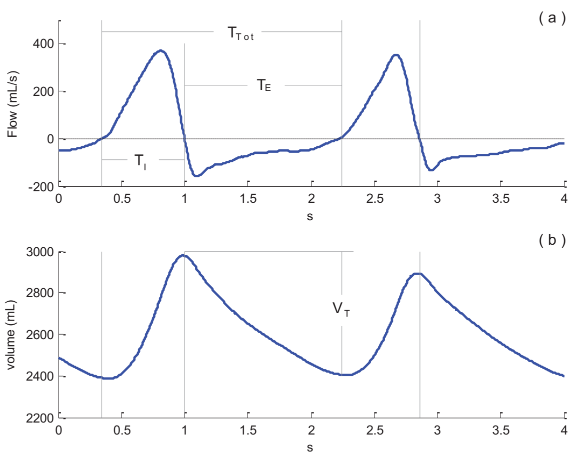

Figure 1. (a) Respiratory flow signal and their time series: inspiratory time (T_I), expiratory time (T_E) and breathing cycle duration (T_{Tot}). (b) Respiratory volume signal and tidal volume (V_T).

C. Modeling techniques

Applying models as AR, ARMA and ARX for each respiratory time series, features as model order, first coefficient, and final prediction error (FPE) were calculated, for each patient [8]. The most relevant parameters were selected for discriminate between different groups of patients. Kruskal-Wallis and Mann-Whitney statistical tests were applied when comparing three and two groups of patients, respectively.

D. Classification methods

The following methods were applied for classification of the three groups of patients. The holdout method was used to validate these classifiers [9].

– *Logistic regression.* Logistic regression (LR) is a type of regression analysis used for predicting the outcome of a categorical criterion variable based on one or more predictor variables. A logistic regression model of *k*-variables can be defined as [10].

$$p = \frac{1}{1+e^{-(\alpha_0+\alpha_1 X_1+\alpha_2 X_2+\cdots+\alpha_k X_k)}} \quad (1)$$

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

– *Linear discriminant analysis.* The linear discriminant analysis (LDA) is used to find a linear combination of features which classify two or more classes of the events. This method maximizes the ratio of between-class variance to within-class variance guaranteeing maximal separation [11]. It has been defined as

$$Y = \mu_0 + \mu_1 X_1 + \mu_2 X_2 + \cdots + \mu_k X_k \quad (2)$$

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

– *Support vector machines.* The support vector machines (SVM) are based on transforming data into a higher dimensional space to convert a complex classification problem into a simpler one that can be solved by a linear discriminant function, known as hyperplane, defined by [12]

$$f(x) = wz + b = \sum_i^L \alpha_i y_i K(x_i, x_j) + b \quad (3)$$

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 [13], [14].

– *Decision tree.* A decision tree is a commonly used data mining algorithm and is used as a predictive model. The principle of the Classification and Regression Trees (CART) method is to look at all possible splits for all variables included in the analysis. The results are in the form of an inverted tree. CART begins with a root node and, through a process of yes/no questions, generates descendant nodes. Some nodes are terminal, meaning that a final determination for classification is reached while other nodes continue to be split until terminal nodes are reached. The inputs are represented by a set of predictor attributes [15], [16].

E. Performance evaluation measures

The quality of the results was analyzed through the accuracy (*Acc*), sensitivity (*Sn*) and specificity (*Sp*) for each case. These measures are built from a confusion matrix, which shows a binary classification where (the values) *tp* are true positive, *fp* false positive, *tn* true negative, and *fn* false negative [17]. These measures are defined by

$$Acc = \frac{t_p + t_n}{t_p + f_p + t_n + f_n} \;;\quad Sn = \frac{t_p}{t_p + f_n} \;;\quad Sp = \frac{t_n}{f_n + t_n} \quad (4)$$

III. RESULTS

The most statistically significant parameters obtained were expiratory time (T_E), inspiratory time (T_I), breathing duration (T_{Tot}), and rapid shallow index (f/V_T). The best results obtained with autoregressive models (AR) were found with the model order in these time series. Additionally, the first coefficient of these series also presented significant differences between the groups S, F and R.

The mean values of the ARMA (*p,q*) model order *q,* applied to T_{Tot}, T_I and T_E, tended to be higher in group S than in Group F. T_E resulted the most relevant parameter (p = 0.02). No one of the parameters of group R presented statistically significant differences. The most important results were obtained applying the ARMA model to T_{Tot}, T_I, T_E and f/V_T time series. The final prediction error (FPE) showed significant differences in breathing pattern between the three groups.

In summary, the expiratory time, inspiratory time, breathing cycle duration and rate of rapid shallow index were the time series that showed the best differences between S, F and R groups using the mean value, AR model order, AR first coefficient, and FPE of ARMA model variables. The performance of these time series was evaluated with the four classification methods used in this work (Table I).

TABLE I

THE MOST RELEVANT PARAMETERS OBTAINED WITH THE AUTOREGRESSIVE MODELS THAT CHARACTERIZED THE RESPIRATORY BREATHING PATTERN

Time serie	*Parameter*	*ID*	*p-value*
Expiratory time (T_E)	Mean	X_1	< 0.0001
	AR model order	X_2	< 0.001
	First coefficient AR model	X_3	< 0.005
	ARMA model FPE	X_4	< 0.01
Inspiratory time (T_I)	Mean	X_5	< 0.0005
	AR model order	X_6	< 0.001
	First coefficient AR model	X_7	< 0.005
	ARMA model FPE	X_8	< 0.005
Breathing during (T_{Tot})	Mean	X_9	< 0.0005
	AR model order	X_{10}	< 0.001
	First coefficient AR model	X_{11}	< 0.005
	ARMA model FPE	X_{12}	< 0.01
Rapid shallow index (f/V_T)	Mean	X_{13}	<0.05
	AR model order	X_{14}	< 0.01
	First coefficient AR model	X_{15}	< 0.01
	ARMA model FPE	X_{16}	< 0.05

The results obtained when using all parameters related to T_E (mean, AR model order, first coefficient of AR model, and ARMA model FPE) using the four classifiers, showed accuracy close to 86%, with different values of specificity and sensitivity (Table II).

The performance of the classifiers using only parameters related to T_I, showed values of precision, sensitivity and specificity lower than those obtained with the T_E.

TABLE II

ACCURACY, SENSITIVITY AND SPECIFICITY OBTAINED WITH CLASSIFIERS AS LOGISTIC REGRESSION, LINEAR DISCRIMINANT, SUPPORT VECTOR MACHINES AND DECISION TREE USING PARAMETERS RELATED TO EXPIRATORY TIME

Method	*Acc*	*Sn*	*Sp*
Logistic Regression	0.86	0.92	0.70
Linear Discriminant	0.86	0.90	0.74
SVM	0.85	0.95	0.61
Decision tree	0.85	0.87	0.79

Table III shows the results obtained using the breathing duration parameter, better than those obtained with inspiratory time, but worse than those obtained with the expiratory time. The best accuracy, sensitivity and specificity were obtained using decision tree method.

The f/V_T time series showed values close to 90% for the accuracies and sensitivities, but low for specificities, in all classifiers methods.

TABLE III

ACCURACY, SENSITIVITY AND SPECIFICITY OBTAINED WITH CLASSIFIERS AS LOGISTIC REGRESSION, LINEAR DISCRIMINANT, SUPPORT VECTOR MACHINES AND DECISION TREE USING PARAMETERS RELATED TO BREATHING DURATION

Method	*Acc*	*Sn*	*Sp*
Logistic Regression	0.71	0.85	0.37
Linear Discriminant	0.72	0.77	0.53
SVM	0.72	0.88	0.34
Decision tree	0.83	0.93	0.58

We evaluated all possible combinations of the parameters listed in Table I by identifying the best performance of classifiers. The best results applying logistic regression, linear discriminant analysis and support vector machines classifiers were obtained for the combination of the mean expiratory time (X_1), the first coefficient of the expiratory time (X_3) and the first coefficient of rapid shallow index (X_{15}) (Table IV).

TABLE IV

ACCURACY, SENSITIVITY AND SPECIFICITY OBTAINED WITH LOGISTIC REGRESSION, LINEAR DISCRIMINANT, AND SUPPORT VECTOR MACHINES USING MEAN OF T_E (X_1), FIRST COEFFICIENT AR MODEL OF T_E (X_3), AND FIRST COEFFICIENT AR MODEL OD F/V_T (X_{14})

Method	*Acc*	*Sn*	*Sp*
Logistic Regression	0.89	0.94	0.75
Linear Discriminant	0.88	0.93	0.80
SVM	0.88	0.96	0.66

The better performance was obtained for decision tree classifier, using the mean of the expiratory time (X_1), the order of the AR model at the expiratory time (X_2), the breathing duration (X_{10}), and the rapid shallow index (X_{14}), with an accuracy of 93%, 98% sensitivity and 82% specificity. Table V shows the most important features of this decision tree method.

TABLE V

DECISION TREE CHARACTERISTIC OBTAINED USING THE MEAN OF T_E (X_1) AND THE MODEL ORDER AR OF THE T_E (X_2), T_{TOT} (X_{10}) AND F/V_T (X_{14}).

Node	S (%)	F (%)	Total (%)	Forecast category	Parent node	Param.	Sig.[1]	Values segment.
0	71.2	28.8	100	S	0	X_2	0.000	
1	5.3	94.7	14.4	F	0	X_2	0.000	≤1.0
2	82.3	17.7	85.6	S	2	X_{14}	0.000	>1.0
3	100	0.0	39.4	S	2	X_{14}	0.000	≤10.0
4	42.9	57.1	10.6	F	2	X_{14}	0.000	(10.0 14.0]
5	74.5	25.5	35.6	E	2	X_1	0.000	>14.0
6	0.0	100	5.3	F	4	X_1	0.018	≤1.136
7	85.7	14.3	5.3	S	4	X_1	0.018	>1.136
8	92.3	7.7	19.7	S	5	X_{10}	0.004	≤12.0
9	14.3	85.7	5.63	F	5	X_{10}	0.004	(12.0 31.0]
10	71.4	28.6	10.6	S	5	X_{10}	0.004	>31.0

[1]with Bonferroni correction

IV. CONCLUSIONS

The respiratory pattern can be characterized through the respiratory time series as expiratory time (T_E), inspiratory time (T_I), breathing duration (T_{Tot}), and rapid shallow index (f/V_T). Also it can be characterized by autoregressive models, such as AR or ARMA using parameters related to model order and the first autoregressive coefficient. It is notable the effect of the parameters associated with autoregressive models over the performance of the classifiers studied in this work, mainly, the model order and the first coefficient at the autoregressive AR model.

Classifiers as logistic regression, discriminant linear, support vector machines, and decision trees has been studied in order to determine the best parameters that classify the three different groups of patients.

The best results for the first three methods were obtained considering the parameters mean T_E, first coefficient of AR model of T_E, and first coefficient of AR model for f/V_T. The accuracy achieved with these three methods was 88%, with sensitivities between 93% and 96%, but with low specificities.

The best performance was obtained with decision tree method, an accuracy of 93%, 98% sensitivity and 82% specificity, with the mean and the order of AR model of expiratory time, the breathing duration, and the rapid shallow index.

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