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Analysis of Roots in ARMA Model for the Classification of Patients on Weaning Trials

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***Abstract*— One objective of mechanical ventilation is the recovery of spontaneous breathing as soon as possible. Remove the mechanical ventilation is sometimes more difficult that maintain it. This paper proposes the study of respiratory flow signal of patients on weaning trials process by autoregressive moving average model (ARMA), through the location of poles and zeros of the model. A total of 151 patients under extubation process (T-tube test) were analyzed: 91 patients with successful weaning (GS), 39 patients that failed to maintain spontaneous breathing and were reconnected (GF), and 21 patients extubated after the test but before 48 hours were reintubated (GR). The optimal model was obtained with order 8, and statistical significant differences were obtained considering the values of angles of the first four poles and the first zero. The best classification was obtained between GF and GR, with an accuracy of 75.3% on the mean value of the angle of the first pole.**

I. Introduction

Mechanical ventilation provides support to patients with respiratory failure. Liberation from mechanical ventilation is a common clinical practice, and there are different protocols for removal of ventilator support. The need for accurate prediction applies to all phases of weaning, beginning with reductions in mechanical support, as patients are increasingly able to support their own breathing, followed by trials of unassisted breathing, which often precede extubation, and ending with this [1]. Withdrawal of mechanical ventilation should be performed as soon as autonomous respiration can be sustained. Both unnecessary delay and premature weaning may have adverse effects on patients' outcome, prolonging mechanical ventilation and duration of intensive care unit stay [2]. Weaning process represents a period of transition from mechanical ventilation to spontaneous breathing, and is associated with a change in autonomic activity [3]-[5]. When mechanical ventilation is discontinued, up to 25% of patients have respiratory distress severe enough to require reinstitution of ventilator support [6]. Several weaning indices have been studied for estimation of weaning readiness. The variability of breath duration is non-random and may be explained by a central neural mechanism or by instability in the chemical feedback loops [7]. Different studies have been performed in order to detect which physiological variables identify readiness to undertake a weaning trial [8]-[10]. In our previous work we characterized the respiratory pattern of patients in weaning process through variability of respiratory time series [11], [12].

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The spectral analysis is a tool widely used to assess many types of biomedical signals. Several studies have been given for the estimation of AutoRegressive (AR) and Moving Average (MA) models. Processes with spectral poles or narrow peaks are preferably described with AR models. The MA models are suitable to describe processes with spectral zeros or narrow valleys with only a few parameters. The AR models would 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 has used long AR models in MA estimation, and this method can produce accurate estimates if the order of that AR model is correctly chosen [13]. The MA method of Durbin is based on the theoretical and asymptotical equivalence of AR (∞) and MA (q) processes. In practice, estimates of the finite-order AR models have to 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 is estimated [14], [15].

The quality of selected model depends on the sample size used for estimation, on the number of observations, on the estimation algorithm, and on the order selection criterion. Several autoregressive estimation algorithms have been developed [16]. The asymptotical theory is more or less the same for all these different estimation algorithms. Many criteria exist for order selection like the final prediction error (FPE), asymptotic information criteria (AIC), autoregressive transfer function criterion (CAT), and different variants of these have been reported and studied. The penalty for estimating more parameters becomes a function of the sample size in the consistent method. Many asymptotical order selection criteria can be written as a single generalized information criterion (GIC) with different values for the penalty factor [16], [17]. A test for any model selection and estimation procedure is to apply it to the selection of a model class, and then analyse the result under the presumption that the data are generated by a model in one of the classes [18]. We propose the study of the respiratory flow signal using

ARMA model with GIC criteria, for the classification of the different groups of patients on weaning trials process, through the poles and zeros of their models.

II. METHODOLOGY

A. Dataset

Respiratory flow signals were measured in 151 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 included in this study according to standard indices that initially determine the spontaneous breathing test: resolution of the etiology of respiratory failure (with inspired oxygen fraction [FiO_2] $\leq$ 0.4, oxygen saturation [SO_2] $\geq$ 90% and the need for positive end-expiratory pressure [PEEP $\leq$ 5 cm to H_2O]), hemodynamic stability (absence of myocardium ischemia and/or heart failure, cardiac frequency $\leq$ 140 bpm, and stable arterial tension with tolerance of a reduction in inotropic support), and adequate respiratory muscle function (acceptable respiratory rate).

Using clinical criteria based on the T-tube test, the patients were disconnected from the ventilator and maintained spontaneous breathing through an endotraqueal tube during 30 min. The records were obtained few minutes after disconnection. 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 GS, 91 patients (60 male, 31 female, aged 65±17 years) with successful weaning; group GF, 39 patients (24 male, 15 female, aged 67±15 years) that failed to maintain spontaneous breathing; and group GR, 21 patients (11 male, 10 female, aged 68±14 years) who had successful weaning trials, but required reintubation in less than 48 h.

Respiratory flow signal was acquired using a pneumo-tachograph (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 signals were resampled to 25 Hz.

B. *Autoregressive moving-average model* (ARMA)

These models are more accurate than autoregressive models (AR) and can give better description of the dynamic characteristics of the system. ARMA (p,q) process x_n can be written as [14]

$$\begin{aligned} &x_n + a_1\, x_{n-1} + \cdots + a_p\, x_{n-p} = \\ &\varepsilon_n + b_1\, \varepsilon_{n-1} + \cdots + b_q\, \varepsilon_{n-q} \quad , \end{aligned} \tag{1}$$

where ε_n is a random white noise process with zero mean and variance $\sigma_\varepsilon{}^2$; p corresponding to autoregressive terms and q moving-average terms.

This ARMA (p, q) process becomes AR for $q = 0$ and MA for $p = 0$.

C. *Poles and zeros of the model*

The roots of the AR and MA polynomials $A(z)$ and $B(z)$ are denoted, respectively, by the poles and zeros of the ARMA(p, q) process as [14]

$$\begin{aligned} A(z) &= 1 + a_1\, z^{-1} + \cdots + a_p\, z^{-p} \\ B(z) &= 1 + b_1\, z^{-1} + \cdots + b_q\, z^{-q} \end{aligned} \tag{2}$$

Here, z is known as the shift operator. The processes are called stationary if all the poles are strictly within the unit circle, and they are invertible if all the zeros are within the unit circle. The poles of the model represent the higher peaks of the magnitude, in one specific frequency. The zeros of the model show the attenuation of the signal in determined frequency.

D. *Power spectral density*

The parametric power spectrum $h(\omega)$ of ARMA(p, q) model is computed for $-\pi < \omega \leq \pi$ with [14]

$$h(\omega) = \frac{\sigma_\varepsilon^2}{2\pi} \frac{\left| Be^{j\omega} \right|^2}{\left| Ae^{j\omega} \right|^2} = \frac{\sigma_\varepsilon^2}{2\pi} \frac{\left| 1 + \Sigma_{i=1}^{q} b_i\, e^{-j\omega i} \right|^2}{\left| 1 + \Sigma_{i=1}^{p} a_i\, e^{-j\omega i} \right|^2} . \tag{3}$$

The model is estimated with Yule-Walker method. The model order is selected with generalized information criterion (*GIC*) for the penalty factor α as [14]

$$GIC(p,\alpha) = \ln \sigma_\varepsilon^2 + \frac{\alpha\, p}{N} \quad , \tag{4}$$

where N is the sample size.

To select a model order, GIC(p, α) is determined for all orders $p = q$ between 0 and some maximum order L. The order with minimum value of the criterion is selected. The penalty factor α = 3 was selected [16].

D. *Statistical analysis*

Statistical analysis was performed using SPSS program. Data are expressed as mean ± SD. Differences in mean values were tested by Kruskal-Wallys and U-Mann-Whitney test, for three and two groups, respectively. Classification between different groups was performed using a discriminant lineal analysis with leave-one-out cross-validation. $p < 0.05$ was considered significant.

III. RESULTS

A model order 8 showed an optimal representation of the poles and zeros that characterize respiratory flow signal. Figure 1 illustrates the position of the poles and zeros of the respiratory flow signals for each group of patients: GS, GF and GR. The results show four poles and one zero as the most discriminant in each group of patients.

Table I shows mean and standard deviation of the angles and radios of those poles and zeros for each group of patients.

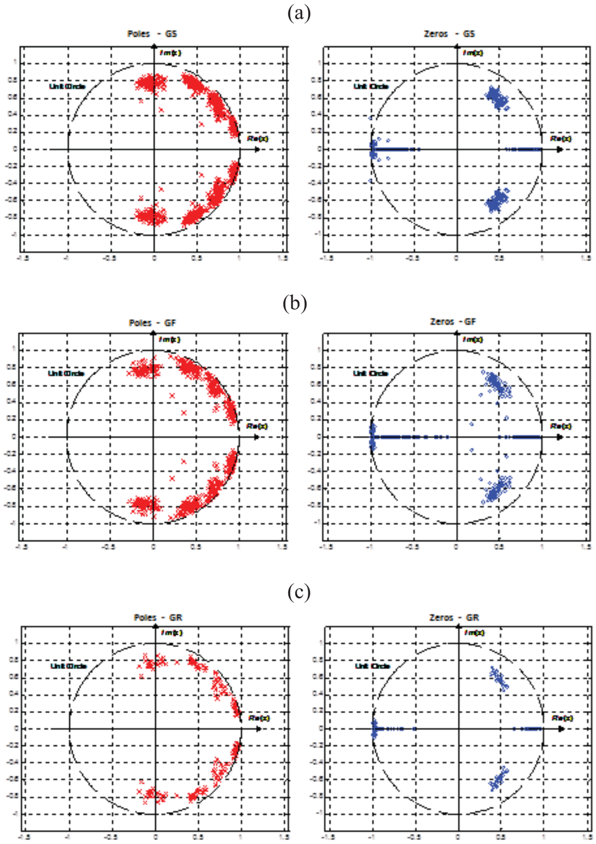

Figure 1. Poles and zeros of the ARMA model, order 8, applied to respiratory flow signal in (a) group GS, (b) group GF, and (c) group GR.

TABLE I. MEAN ± STANDARD DEVIATION OF THE ANGLES AND RADIOS FOR EACH GROUP OF PATIENTS OF THE MOST RELEVANT POLES AND ZEROS

		GS	GF	GR
Pole	Angle - 1 (rad)	0.27±0.02	0.31±0.03	0.26±0.02
	Angle - 2 (rad)	0.61±0.06	0.67±0.06	0.60±0.07
	Angle - 3 (rad)	1.03±0.08	1.08±0.09	1.02±0.08
	Angle - 4 (rad)	1.60±0.10	1.67±0.11	1.60±0.11
Zero	Angle - 1 (rad)	0.88±0.20	0.87±0.20	0.88±0.19
Pole	Radio - 1	0.96±0.03	0.95±0.04	0.96±0.04
	Radio - 2	0.90±0.05	0.91±0.05	0.89±0.06
	Radio - 3	0.89±0.05	0.89±0.05	0.89±0.06
	Radio - 4	0.78±0.05	0.78±0.06	0.77±0.06
Zero	Radio - 1	0.77±0.09	0.78±0.09	0.77±0.09

Tables II and III show the angles and radios that presented statistically significant differences. Comparisons were made considering the three groups at a time, comparing the combination of two groups and comparing each group with the remaining patients.

From the ARMA model parameters, the PSD was obtained for each patient. Figure 2 presents the average PSD of each group of patients. The peaks correspond with the position each one of the four poles.

TABLE II. STATISTICALLY SIGNIFICANT DIFFERENCES BETWEEN THE MEAN VALUES OF ANGLES

		Pole				Zero
		Angle 1	**Angle 2**	**Angle 3**	**Angle 4**	**Angle 1**
***p* - value**	GS GF GR	<0.0005	<0.0005	<0.0005	<0.0005	n.s.
	GS vs GF	<0.0005	<0.0005	<0.0005	<0.0005	n.s.
	GF vs GR	0.002	0.008	0.011	0.025	n.s.
	GS vs GR	n.s.	n.s.	n.s.	n.s.	n.s.
	GS vs All	0.001	0.002	0.002	<0.0005	n.s.
	GF vs All	<0.0005	<0.0005	<0.0005	<0.0005	n.s.
	GR vs All	n.s.	n.s.	n.s.	n.s.	n.s.

TABLE III. STATISTICALLY SIGNIFICANT DIFFERENCES BETWEEN THE MEAN VALUES OF RADIOS

		Pole				Zero
		Radio 1	**Radio 2**	**Radio 3**	**Radio 4**	**Radio 1**
***p* - value**	GS	n.s.		n.s.	n.s.	n.s.
	GF		0.024		n.s.	n.s.
	GR				n.s.	n.s.
	GS vs GF	n.s.	0.010	n.s.	n.s.	n.s.
	GF vs GR	n.s.	n.s.	n.s.	n.s.	n.s.
	GS vs GR	n.s.	n.s.	n.s.	n.s.	n.s.
	GS vs All	n.s.	0.046	n.s.	n.s.	n.s.
	GF vs All	n.s.	0.007	n.s.	n.s.	n.s.
	GR vs All	n.s.	n.s.	n.s.	n.s.	n.s.

The frequency with the maximum PSD (*f*max) was obtained for each group. Table IV shows that *f*max of group GF is higher than that of group GS and group GR. Table V shows the *p*-values when comparing the different groups of patients (GS, GF and GR), through the dominant frequency of PSD. The results indicate that there are significant differences between all these comparisons, except between group GS and group GR.

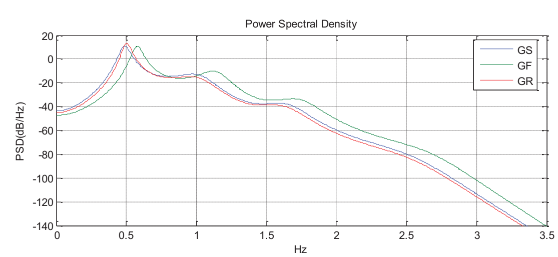

Figure 2. Mean of power spectral density of the respiratory flow signal for group GS, group GF, and group GR.

TABLE IV.
MEAN ± STANDARD DEVIATION OF THE MAXIMUM PEAK FOR EACH GROUP OF PATIENTS

	f max (Hz)
GS	0.440 ± 0.035
GF	0.537 ± 0.053
GR	0.424 ± 0.036

TABLE V
STATISTICALLY SIGNIFICANT DIFFERENCES OF THE PREDOMINANT FREQUENCY WHEN COMPARING THE DIFFERENT GROUPS OF PATIENTS

	***p* - valor**
GS GF GR	<0.0005
GS vs. GF	<0.0005
GF vs. GR	0.001
GS vs. GR	n.s.
GS vs. (GF + GR)	<0.0005
GF vs. (GS + GR)	<0.0005
GR vs. (GS + GF)	0.048

The most significant parameters obtained from the ARMA model, are related to poles and are: the angles 1, 2, 3 and 4, and the radio 2. The best classification (discriminant linear analysis) with all these relevant parameters was of 69.5% when comparing groups GS and GF, and 69.7% for groups GF and GR.

When compared the groups considering only the most relevant parameter, the angle of the first pole, we obtained that 68.4% of patients were correctly classified when comparing groups GS and GF, and a 75.3% of patients when comparing groups GF and GR.

IV. CONCLUSION

The results suggest that the group GS and the group GF can be classified with the poles and the zeros of the ARMA model, and with the frequency that characterize the spectrum of the respiratory flow signal.

An interesting result is obtained when comparing the groups GF and GR, with an accuracy of 75.3%. In the clinical research there are not clear indices for the classification of the reintubated patients.

As a first study, these results allow considering the roots in ARMA model as a promising tool to characterize the respiratory flow signals of these different groups of patients. A further evaluation of the methods performance should be done validating it by a higher number of patients, and including other clinical parameters.

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