Methodology for Determine the Moment of Disconnection of Patients of the Mechanical Ventilation using Neural Network

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ABSTRACT

The process of weaning from mechanical ventilation is one of the challenges in intensive care units. In this paper 66 patients under extubation process (T-tube test) were studied: 33 patients with successful trials and 33 patients who failed to maintain spontaneous breathing and were reconnected. Each patient was characterized using 7 time series from respiratory signals, and for each serie was extracted 4 statistics data. Two types of Neural Networks were applied for discriminate between patients from the two groups: radial basis function and multilayer perceptron, getting better results with the second type of network.

Keywords: Mechanical Ventilation, Time series from respiratory signals, Neural Networks.

RESUMEN

El proceso de destete de la ventilación mecánica es uno de los desafíos en las unidades de cuidados intensivos. En este trabajo se esturiaron 66 pacientes en proceso de extubación (Tubo en T): 33 pacientes con éxito de los ensayos y 33 pacientes que no lograron mantener la respiración espontánea y se vuelven a conectar. Cada paciente fue caracterizado utilizando 7 series de tiempo de las señales de las vías respiratorias, y para cada serie se evaluaron 4 datos estadísticos. Dos arquitecutras de redes neuronales se aplicaron para discriminar entre pacientes de los dos grupos: red de base radial y perceptrón multicapa, obteniendo mejores resultados con el segundo tipo de red.

Palabras claves: Ventilación mecánica, Series de tiempo para señales respiratorias, redes neuronales

1. INTRODUCTION

Mechanical ventilators, which are often also called respirators, are used to artificially ventilate the lungs of patients who are unable to naturally breathe from the atmosphere. There are two main divisions of mechanical ventilation: invasive ventilation and non-invasive ventilation. There are two main modes of mechanical ventilation within the two divisions: positive pressure ventilation, where air (or another gas mix) is pushed into the trachea, and negative pressure ventilation, where air is essentially sucked into the lungs (Patroniti, 2011).

Discontinuation of mechanical ventilation, also called weaning or extubation, should be performed as soon as autonomous respiration can be sustained. It is one of the most challenging problems in intensive care units. Despite advances in mechanical ventilation and respiratory support, the science of determining if the patient is ready for extubation is still very imprecise. A failed weaning trial is discomforting for the patient and may induce significant cardiopulmonary distress. When mechanical ventilation is discontinued, up to 25 percent of patients have respiratory distress severe enough to necessitate reinstitution of ventilatory support. Hence the need for a more accurate prediction of the optimal disconnection time, which is extended to the whole weaning process (Meade et al., 2001 - Tobin , 2001). The variability of breathing pattern is not random and can be explained by central neural mechanisms or instability of the feedback loops (Benchetrit, 2000). This variability was analyzed previously in (Bruce, 1996 - Tobin et al., 1988 – Khoo, 2000 - Caminal et al., 2004).

The purpose of this work is to characterize the variability of the respiratory pattern of patients on weaning trials using neural network techniques, providing enhanced information in order to identify patients with successful spontaneous breathing trials and patients with unsuccessful trials. Neural networks are sophisticated statistical techniques capable of modeling extremely complex functions. Some authors have proposed methodologies to give solution to this problem, using this same technique (Giraldo et al., 2006), support vector machine (Giraldo et al., 2006), or cluster analysis (Arizmendi et al., 2009).

2. ANALYZED DATA

In this study, respiratory flow signals were measured in 66 patients under mechanical ventilation and extubation process (database WEANDB). The patients were recorded in the Departments of Intensive Care Units at Santa Creu i Sant Pau Hospital, Barcelona, Spain, and Getafe Hospital, Getafe, Spain, according to the protocols approved by the local ethics committees. The Patients were submitted under T-tube test, disconnected from the ventilator and maintained spontaneous breathing through an endotraqueal tube during 30 min. According to the clinical criteria, the patients were classified into two groups: group A, 33 patients whose T-tube test was overcome successfully, and group B, 33 patients who failed the test and therefore could not be extubated.

The respiratory flow was obtained with a pneumotachograph (Datex-Ohmeda monitor with variable reluctance transducer) connected to an endotracheal tube. The signals were recorded at a sampling frequency of 250 Hz during 30 minutes.

The respiratory pattern can be characterized by the following time series: inspiratory time (TI), expiratory time (TE), breathing cycle duration (TTot), tidal volume (VT), inspiratory fraction (TI /TTot), mean inspiratory flow (VT/TI) and rapid shallow breathing (f/VT), were f is respiratory rate. The figure 1 shows a respiratory signal and the respective parameters.

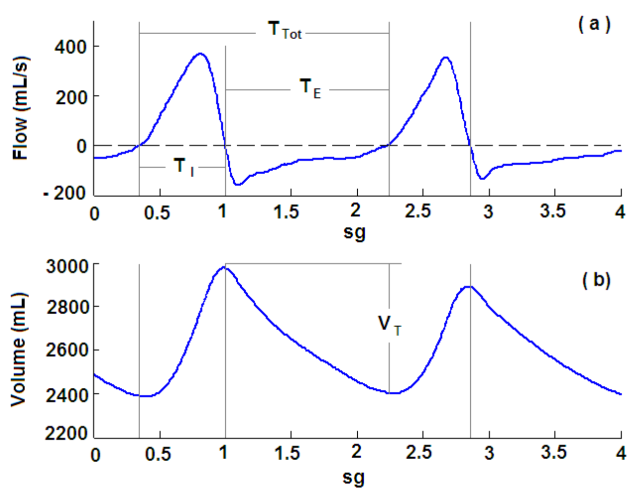

Figure 1. (a) Respiratory flow signal and their time series: inspiratory time (TI), expiratory time (TE) and breathing cycle duration (TTot). (b) Respiratory volume signal and tidal volume (VT)

3. METHODOLOGY AND RESULTS

For each one of the time series was evaluated four statistics data:

- *Arithmetic mean (M).* It is the central tendency of a collection of numbers taken as the sum of the numbers divided by the size of the collection.
- *Standard deviation (SD).* It shows how much variation or dispersion exists from the average. A low standard deviation indicates that the data points tend to be very close to the mean; high standard deviation indicates that the data points are spread out over a large range of values.
- *Interquartile range (IQR).* It is equal to the difference between the upper and lower quartiles.
- *Kurtosis (K).* It is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak.

In this way, 28 new time series were obtained for each patient (Fig. 2), that are the features of the system. The 28 time series are normalized by Equation 1, because each variable showed a different range.

$$x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

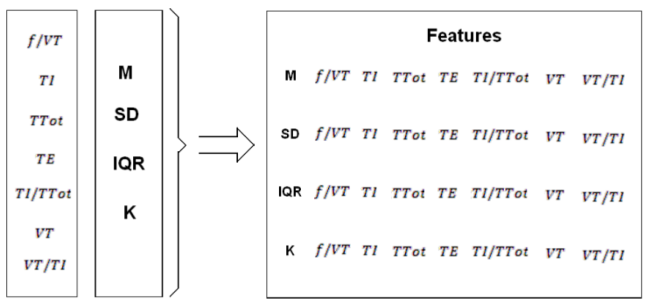

Figure 2. Representation of 28 features for each patient with seven respiratory time series

3.1 RADIAL BASIS FUNCTION NETWORK

Radial basis function (RBF) networks have advantages of easy design, good generalization, strong tolerance to input noise, and online learning ability. A RBF has an input layer, a hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron.

Of the 66 files of the database, 40 files were designated for the training of the neural network and 26 for the stage of validation. The network architecture was of four input neurons and one neuron of output, it indicates whether the patient should be disconnected of mechanical ventilation system. The newrb command, of the Neural Network Toolbox – Matlab (Beale et al., 2012), was used for to train the neural network. A configuration parameter of the function is the *spread*, a factor that is proportional to the width of the Gaussian function. The larger spread is, the smoother the function approximation. Too large a spread means a lot of neurons are required to fit a fast-changing function. Too small a spread means many neurons are required to fit a smooth function, and the network might not generalize well. Since each patient is characterized with 28 series in time and it is desired to set four input variables for the neural network, it has 20,475 possible combinations of variables. An algorithm was developed for to select among the 20,475 combinations and for each group of variables was modified the spread, of zero to one.

As result was obtained that the combination with the lowest mean squared error (MSE) was TI (Arithmetic mean), VT /TI (Arithmetic mean), TE (Standard deviation) and VT /TI (Standard deviation). The value of spread parameter was 0.2 with a MSE equal to 0.23 in the validation stage. The figure 3 shows the variation of MSE index in function of spread parameter, for the selected combination. The results of the validation stage are shown in table 1.

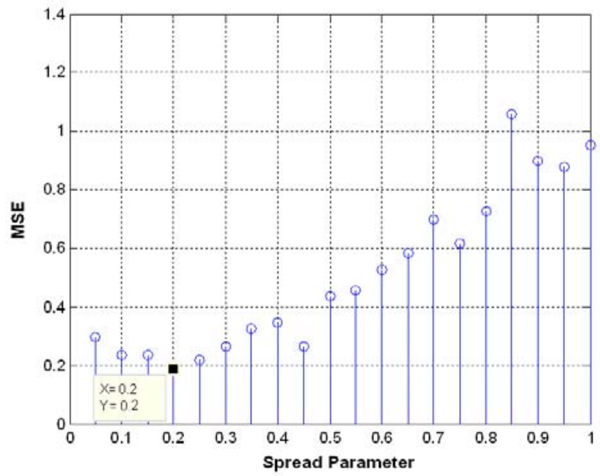

Figure 3. Mse Index vs. Spread Parameter

Table 1. Results of the validation stage - RBF

	Group A	Group B	Not find solution
Group A (13 Patients)	9	2	2
Group B (13 Patients)	2	11	0

3.2 MULTILAYER PERCEPTRONS

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network.

The network architecture was of four input neurons, one hidden layer and one neuron of output. The newff command, of the Neural Network Toolbox - Matlab, was used for to train the neural network. An algorithm was developed for to select among the 20,475 possible combinations and for each group of variables was modified the number of neurons in the hidden layer, of one to eleven (figure 4).

The best combination of variables was VT (Arithmetic mean), TTot (Standard deviation), VT /TI (Standard deviation) and TTot (Kurtosis) with two neurons in the hidden layer. El MSE was of 0.0385 and in the table 2 is shown the results of validation stage.

Table 2. Results of the validation stage - MLP

	Group A	Group B
Group A (13 Patients)	12	1
Group B (13 Patients)	0	13

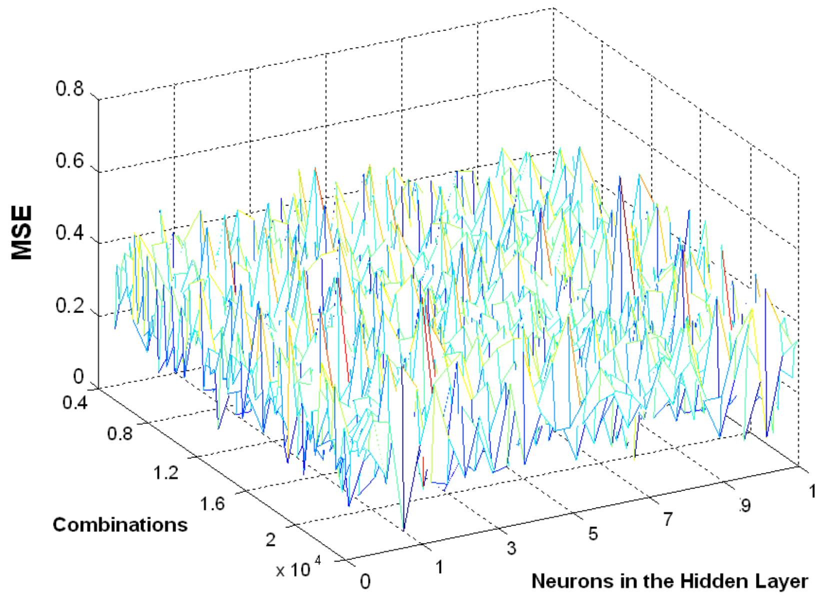

Figure 4. Neurons in the hidden Layer of Neural Network vs. Combinations

4. CONCLUSIONS

A methodology based on neural networks has been applied for determine the moment of disconnection of patients of the mechanical ventilation, analyzing the respiratory pattern. The best result was obtained with the multilayer perceptron, the combination V_T (Arithmetic mean), T_{Tot} (Standard deviation), V_T/T_I (Standard deviation) and T_{Tot} (Kurtosis). Other variables give results similar, as shown in Figure 4, but there are not specific and reproducible criteria clearly established for determining the best combination; in this paper as selection criteria it used the mse (mean squared error) index. This diagnosis is a critical task for medical experts in hospital environments. Most decisions in this context bound to be made on the basis of doctors' experience.

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