Decision support tools in the ICU; ventilation management for patients with COPD.

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Abstract: **Clinical personnel experience and expertise, case mix, task complexity and medical errors in the ICU, are the main factors affecting ventilation management efficiency. There are increasing evidence to support the need of "*automating*" the process of ventilation management, not only in terms of efficiency, but also in terms of health care cost containment. Patients with chronic obstructive pulmonary disease (COPD) are characterized by increased work of breathing (WOB) and ventilatory muscle dysfunction. Since patients' needs are not static, ventilator settings have to be adjusted regularly. The aim of the present study was the development and evaluation of a neural network driven fuzzy advisor that utilizes non-invasively acquired parameters for the determination of the appropriate tidal volume (V_T) and respiration frequency (RR) ventilator settings for COPD patients. Forty three (43) hours of non-invasively monitored physiology parameters and ventilator settings, from four (4) different COPD patients ventilated in control mode, were collected in two (2) General Hospitals in Greece. Recorded data were randomly allocated into two sets, namely training set (60%) and evaluation set (40%). neural network driven fuzzy advisor was developed and trained, by employing the training set. The controller utilizes non-invasively measured parameters, for suggesting V_T and RR settings. The developed system was tested against evaluation set. The Mean Square Error of the tidal volume and the respiration rate was 0.222 ml/Kgr and 1.21 breaths per minute (bpm) respectively.**

I. Introduction

Mechanical ventilation support is provided to critically ill ICU patients who are unable to maintain gas exchange. ICU clinicians monitor and evaluate cardio-respiratory related physiology parameters, in order to evaluate adequacy of mechanical ventilation. Since a patient's needs are continuously changing, clinicians have to adapt the ventilation strategy and drug administration on a regular basis. This ongoing process is described as ventilation-respiration management. Patients with chronic obstructive pulmonary disease (COPD) are characterized by increased work of breathing (WOB) and ventilatory muscle dysfunction due to chronic airflow limitation from inflammation, airway hyperactivity, secretions and loss of the structural integrity of the lung parenchyma [Hess D.R 2002].

II. Background

"In the United States, the number of patients who died from medical error alone is equivalent to one airplane crash every day of the year" [Wysocki, 2007]. Anesthetic incidents in the operating room are attributed between 70 to 82% to a human error [Dhillon, 2000]. These two research results picture the "cost" of incorrect human decision making in medicine. The problem is magnified in medical areas where life sustaining equipment is used.

In the ICU, the changes performed on drug administration and ventilation settings related to ventilation adequacy, are made based on a strategy. The strategy could be formed based on knowledge, expertise and experience, or based on available guidelines and protocols, or more often as a combination of both.

Hancock and Durham [Hancock H.C, Durham L., 2007] addressed the theoretical background of clinical decision making. According to the authors three different approaches are described in the literature: Analytical methodology, which is a linear process involving assessment of alternatives and selection of a course of action. Intuition, which is a holistic consideration of situations based on experience; practitioners have developed knowledge structures, enabling them to respond to a problem with the use of accumulated experience. Cognitive continuum theory which suggests that decision making is somewhere between the analytical and intuitive ends.

Taylor [Taylor F, 2006] in his research on decision making process in weaning patients reported that ICU staff utilizes in action different approaches in decision making. Hypothetico-deductive approach, Concept of balance, Pattern matching, Intuition and trial and error, were used by the clinical staff participated in the research.

The need of protocols and guidelines is generated by the multi-parametric nature of the ventilation management process. Carson et al [Carson E.R. et al 1991] focus on the need of converting measured data into information for clinicians. Their argument is supported by the substantial increase in the number of measured, derived and alarm parameters in the ICU, over the past decades. Since humans have limited ability to estimate covariance between multiple variables [Morris A.H, Cook D.J, 1998], guidelines are necessary. Hypothesis, memory recall, prejudice, local cultural factors, local technical abilities and experience are all factors influencing caregiver decisions in the ICU.

Algorithms developed for the ICU setting usually contain fuzzy terms such as “optimize PEEP”, which cannot be translated into executable instructions [Morris A.H, Cook D.J, 1998]. Even more when flow diagrams are developed, it is difficult to implement them in different patient-clinical settings, leading to identical treatment decisions.

A different strategy is adopted according to patient pathology. Although protocols - guidelines have been developed, there are diverse methodologies for dealing with the same problem [Brochard et al., 1994, Butter R et al., 1999, Horst H.M, 1998].

Decision support tools in the ICU, range from simple alerts to sophisticated automatically adjustments on ventilation settings and closed loop ventilation systems [Clemmer, 2004]. Many authors have approached the problem of decision making in the ICU, utilizing different Artificial Intelligence methodologies [Mahfouf M 2006, Kwok H.F et al 2003, Goode K.M, 1993, Wang A et al 2006, Sun Y et al 1994, Nemoto T et al 1999], however only four closed loop systems are commercially available today [Wysocki, 2007].

In relation to the other approaches in ventilation management, the proposed system was designed for specific lung pathology, namely COPD, it was trained with real patient data rather than scenarios/simulation data, and it utilizes as inputs non-invasively acquired parameters, which simplifies its future application in a clinical setting.

The proposed architecture utilizes NN to implement the rule base of a fuzzy system. Although both fuzzy and neural approaches possess remarkable properties when employed individually, their synergism is closer to human intelligence [Tsoukalas L.H, Uhrig R.E, 1997]. The employment of NN in fuzzy systems provides them the ability to learn, while maintaining all the advantages of fuzzy systems.

III. Fuzzy Logic & Artificial Neural Networks.

Fuzzy Rule Based Systems (FRBSs), constitute an extension to classical rule based systems. Fuzzy Sets (FSs), were introduced by Lofti A. Zadeh in 1965 [Cox E, 1994]. Knowledge representation is performed with the use of linguistic variables.

Fuzzy Logic (FL) demonstrates several advantages over other methodologies. It can easily model complex systems, by introducing a development methodology similar to human communication; experts’ knowledge is encoded directly in a form very similar to their decision making process; the RB of a FRBS is evaluated in parallel, thus all decision determinants are considered in the solution of a problem; FL models uncertainty and imprecision in complex models where understanding is limited and/or judgmental.

Neural networks consist of interconnected information processing units called artificial neurons. The structure of a neuron consist of external inputs, synapses, dendrites, a soma and an axon, which transmits output to other neurons [Picton P, 2000]. Inputs are modified by weights, representing the synaptic junctions. Each synaptic output is an input to the soma called dendritic input. Each dendritic input is a transformed version of the external input.

Tagaki and Hayashi [Tagaki H, Hayashi I, 1992], suggested a NN Driven Fuzzy reasoning methodology. According to this strategy a NN is trained from a set of input – output data, not based on their crisp values but rather on the degree of membership to predefined input – output fuzzy sets.

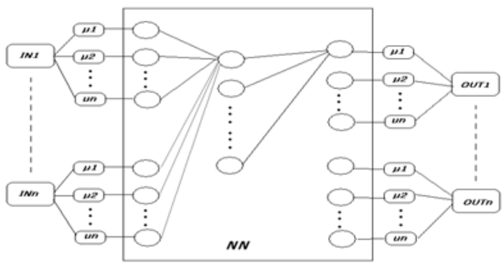

Fig. 1. Architecture of the neural-fuzzy network proposed by XZ Wang et al 1995.

Jang & Gulley developed a toolbox for Matlab®, named Adaptive network based fuzzy inference system (ANFIS), [Jang J.S, Gulley N, 1995], which is appropriate for learning fuzzy systems. ANFIS is based on gradient descent optimization with feed forward NN, for learning single output Tagaki-Sugeno (TSK) systems. ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method.

IV. Methodology

Forty three (43) hours of non-invasively monitored physiology parameters and ventilator settings, from four (4) different COPD ventilated in control mode, were collected in two (2) general hospitals, namely Veteran's General Hospital of Athens (NIMTS), and University Hospital of Heraclion, Crete (PEPAGNI).

We have designed and developed a MatLab (Mathworks®) toolbox for automatically generating Mandani FRBS from available input(s) – output(s) data in excel format.

The toolbox utilizes the NN toolbox of MatLab. The toolbox was named **FU**zzy **N**eural (FUN) and allows for the user to define fuzzy systems' parameters as well as well as NN settings. The structure of the toolbox is based on the architecture proposed by Wang et al [Wang XZ 1997]. Recorded data were randomly divided into training and evaluating sets. Sixty percent (60%) of the available data were used for the training of the NN-FRBS system. The controller utilizes non-invasively measured parameters, namely oxygen saturation (S_pO_2), lung compliance (C) and resistance (R), Peak Inspiratory pressure (PIP) and Plateau pressure ($P_{plateau}$) as inputs for the system. The outputs are suggested values for V_T and RR ventilator settings. V_T was expressed as ml/Kgr, in order to allow comparison between different patients. A more thorough presentation of the advisor system could be found in our report in Tzavaras et al [Tzavaras A et al, 2007].

IV. Evaluation & Results

The NN was trained for 1000 epochs, with the corresponding input-output membership degrees of the training set values. The resulted NN, performed with a mean square error (*mse*) of 0.0012. The *mse* refers to the deviation from the actual membership degrees.

The developed NN-FRBS system was applied to the evaluation set, in order to identify the deviation of the suggested ventilator settings from the recorded clinicians' decisions. The mean square error of the tidal volume and the respiration rate was 0.222 ml/Kgr and 1.21 bpm respectively.

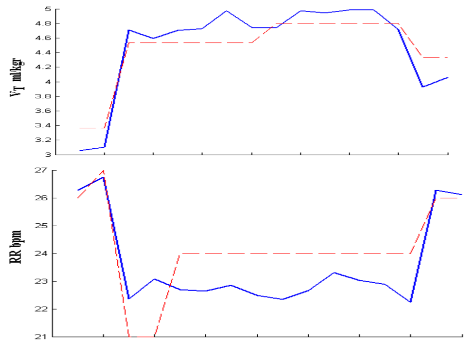

Fig. 2 Top (6a) suggested (solid) vs. recorded (dash) V_T. Bottom (6b) suggested (solid) vs. recorded (dash) RR.

V. Conclusions

The developed method and more specifically the outcome of the Neural Network Driven Fuzzy Logic (FUN) MatLab (Mathworks®) toolbox for automatically generating FRBS from available input(s) – output(s) data in Microsoft Excel ® format, seems to give very good results after this first case study that was based on the data accumulated during forty three hours of non-invasively monitored physiology parameters and ventilator settings, from four different COPD patients ventilated in control mode.

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