Artificial neural networks in the assessment of respiratory mechanics

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INTRODUCTION

If we want to define it synthetically, Connectionism is the attempt to simulate the biological intelligence on a computer. It consists of theories, ideas and computing techniques that represent a revolution in the study of mind and brain. It has developed by the observation that behaviours typical of human learning could be reproduced using networks of numerous simple units (the Artificial Neural Networks).
A connectionist system has the possibility to learn to perform a particular task without needing an a-priori knowledge. This is the difference with the classical artificial intelligence, based on the so-called expert systems. In an expert system it is necessary first to analytically solve a problem, then translate it to a computer, in order to obtain a procedure of calculation. In order to understand what are the limits of expert systems that ANNs can overcome, it is necessary to describe how a connectionist system works. ANNs simulate a network of neurons divided into layers. ANNs are composed of three kind of layers: input layer, hidden layers, output layer. Information enters the net via the input layer and after having propagated through the layers, arrive to the output layer. The net learns by examples. If we want to train an ANN to recognize images, it is necessary to feed it by giving the images at the input and at the same time, the output that we want has to associate to the example. By using particular algorithms (as the error backpropagation algorithm) we modify the connections among the neurons in the intermediate layers, in order to have the right answer when we show an image to the ANN. After the training phase, during which it is possible to monitor the process of learning, ANNs acquire the capacity of generalizing. Like human learning, after the ANN has learnt the paradigmatic examples, it builds an internal representation of the rules it has extracted from the reality. Another property of ANNs is that the learning is "strong". If the network loses a neuron, the overall performance is only slighty affected (the knowledge is in the net of connections and not belonging to some particular neuron). The ANNs have also the capacity of extrapolate way of behaviour in situations that were not presented to them during the learning phase.

REVIEW OF LITERATURE

ANNs can learn different tasks, as confirmed by the increasing amount of literature of the last years. A review on the applications of ANNs to the different fields of medicine was published by The Lancet in 1995[1-3]. ANNs have been used as clinical decision support tools [4-6], for predicting the clinical likelihood of a pathological condition[7] , the chronicity in ICU patients[8;9] or the possible successful weaning from mechanical ventilation[10;11]. ANNs can also analyze signals of various sorts: electrocardiograms[12-16], electromyograms[17], electroencephalograms[18;19], haemodynamic variables recording[20], cardiotocograms[21]. Other examples of utilization are: intelligent alarms for operating rooms based on ANNs[22;23] and use for monitoring the depth of anaesthesia[24]. ANNs have been used as classifiers of heart[25] and lung[26;27] sounds and to support image analysis [28-31].

We are proposing the use of ANNs in the respiratory monitoring of the intensive care units. In this wide field of possible applications, very little work has been done. Leon and Lorini [32] investigated the capability of ANNs to identify spontaneous and pressure support ventilation modes from gas flow and airway pressure signals. Wilks and English[33] used ANNs, in an exploratory experiment, to classify respiratory patterns in effective or not, in order to predict harmful changes of O_2 saturation in infants. Snowden et al.[34], fed an ANN with blood gas parameters and the ventilator settings that determined them, in order to obtain new ventilator settings. However the limit of this study was that they trained an ANN using the rules of an expert system: in this situation ANNs cannot express all their properties. Bright et al.[35] have described the use of an ANN to identify upper airway obstruction (UAO). The ANN was fed with six indices taken from the expiratory limb of a flow-volume loop and the performance obtained was better than human experts at identifying flow loops with UAO. Leon et al.[36] developed a successful ANN-based system to detect esophageal intubation using airways flow and pressure signals. Räsänen and León[37], in a review published for the Yearbook 1995 of Emergency and Intensive Care Medicine, report some experiments (then published in 1998[38]) in which they trained an ANN with the expiratory waveform of injured lungs of dogs. They gave to the ANN the tracings of healty and oleic acid injured lungs and the net had to classify the damage as absent or present (and to what extent). In two studies[39;40] presented at the APICE Congress (held in Trieste, Italy during November 1998), Perchiazzi et al. have shown the possibility to assess the respiratory mechanics of inhomogeneous lungs (in a controlled ventilation setting) using ANN. Those exeperiments were performed using computer simulators of lung function.

EXPERIENCES BY THE AUTHOR

In a first study [41] we evaluated in an animal model: (1) whether ANNs could assess the respiratory system resistance (R_{RS}) and compliance (C_{RS}) using the tracings of pressure at airways opening (P_{AW}), instantaneous inspiratory flow (V'_I) and tidal volume (V_T), during an end-inspiratory hold maneuver and (2) whether it was possible to substitute the animal tracings, in the learning process, by simulations obtained by non-biological models. The ANN had to extract the resistance and the compliance of the respiratory system when fed by curves having an end-inspiratory hold maneuver. An expert manually computed the two variables and these were used for training and testing the ANN. ANN performance was also tested on tracings produced by an electrical analogue of the lung developed via software on a computer.

The ANN trained on animal data and the one trained on the electrical analogue of the lung, were able to learn the relation between the input pattern and the corresponding R_{RS} and C_{RS}. This fact was demonstrated by the performance shown on their respective test groups. In the prospective tests, the performance on C_{RS} remained very good, in both ANNs. However this was not true for R_{RS}. It was possible to conclude that: (1) the estimation of C_{RS} and R_{RS} by ANNs, using the tracings of P_{AW}, V'_I and V_T, during an end-inspiratory hold maneuver, was feasible; (2) The use of tracings obtained by non-biological models in the learning process, has the potential of substituting biological recordings.

In second study[42] we evaluated in an animal model whether ANNs could estimate respiratory system compliance using tracings of pressure and flow at airways opening, without any intervention of an inspiratory hold maneuver during continuous mechanical ventilation. ANN performance could be supervised because compliance was manually computed on a curve belonging to the same train of breaths presenting an End - Inspiratory Hold Maneuver (EIHM). In this study, ANN assessed the C_{RS} with a low error and a low scatter in both healthy and diseased lungs. The amount of error was not statistically different in healthy and sick lung conditions; the ANN error had no dependency from the absolute level of C_{RS}. So it was showed that respiratory system compliance can be estimated by artificial neural networks during volume control mechanical ventilation, without having to stop inspiratory flow.

In a following study[43;44] we tested whether artificial neural networks, fed by inspiratory airway pressure and flow, are able to measure total positive end-expiratory pressure ($PEEP_{tot,stat}$) during ongoing mechanical ventilation using the tracings of pressure and flow at airways opening. The study was designed to create a condition of dynamic pulmonary hyperinflation, by shortening expiratory time in proportion to the time constant of the respiratory system. Measurements were obtained after having added an external resistance and after the induction of acute lung injury by injection of oleic acid. In terms of linear regression, ANN estimated $PEEP_{tot,stat}$ with a very good correlation and a close proximity of the regression line to the identity line. Bland and Altman analysis, showed low bias and scatter of ANN estimation of $PEEP_{tot,stat}$. No dependency was found between estimation error by ANN and $PEEP_{app}$. Considering that $PEEP_{app}$ can be easily read on the ventilator display and that $PEEP_i = PEEP_{tot} - PEEP_{app}$ we concluded that: ANNs can estimate $PEEP_{tot,stat}$ and thus $PEEP_i$ reliably, during ongoing mechanical ventilation, without needing to execute an end-expiratory hold maneuver.

In another experiment [43;45] we evaluated and compared: the robustness of ANN and multi-linear fitting (MLF) methods in extracting respiratory system compliance when facing signals corrupted by perturbations likely to be found in the clinical environment: random noise (RN) or interruptions of the signal continuity - transient disconnection (TD). Our results showed that after the application of RN, ANN and MLF maintain a stable performance, although in these conditions MLF may show better results (lower bias and scatter). ANN have a more stable performance and yield a more robust estimation of C_{RS} than MLF in conditions of transient sensor disconnection.

CONCLUSIONS

Our explorative studies on the application of ANN technology to respiratory mechanics, has shown the feasibility of extracting respiratory mechanics by ANNs.

The difference between a monitoring tool and a research tool, may appear as a trivial matter. It depends on the idea that measuring a physiological variable is simply an *act of research*, an attempt to know the *true number* expressing that particular variable. The consequence is that the *property of the measurement* the scientist tries to obtain is mainly *precision*.

When facing the problem of monitoring a variable or controlling a machine, *precision* is no longer the main property of the measures to aim at. More important become *robustness,* because of the possibility of noise and malfunction of the sensors. Whatever kind of interfacing system between sensors and machines, if developed for working in real life (and not in academic laboratories) it has to be based on a platform that presents this property. In this context the use of ANN may be one possible answer.

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