THE USE OF A PATIENT SIMULATOR FOR KNOWLEDGE ACQUISITION FROM THE CLINICIANS

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Abstract: The first objective of this study is to observe how the clinicians adjust ventilator settings in simulated mechanically ventilated patients. This information was then used to construct the fuzzy rule-bases of a ventilator advisory system. A simulator of patients on artificial ventilation was developed using the MATLAB/SIMULINK environment based on a grey-box mathematical model of the human respiratory system. A graphic user interface (GUI) was designed to improve its usability. Eleven simulated patients were constructed. Each simulated patient consists of 7 to 44 tuned simulated events based on the data recorded in the intensive care unit (ICU) patient data management system (PDMS). Four ICU consultants were invited to participate in the simulation study. The fuzzy input partitions for the rule-bases were derived from the probability distribution of the acceptable input values defined by the clinicians. The rules were derived after correlation analysis of the simulation results and supplemented by the review of the rule-bases by a clinical expert. The rule-bases were validated using independent retrospective clinical data. The performance measures for the FiO_2, PEEP and Ventilatory rate rule-bases were good as in more than 70% of the cases, the fuzzy rule-base output matched exactly the clinician's action recorded in the PDMS. The PINSP rule-base did not perform well. In the future, further tuning of the rule-bases should be done to improve its performance.

Keywords: simulation; human respiratory system; knowledge acquisition; fuzzy systems; intensive care ventilation

1. INTRODUCTION

Artificial ventilation of the lungs is one of the major components of intensive care therapy. The aim of the artificial ventilation is to deliver oxygen to the tissues and to remove carbon dioxide when the patient's lungs are not able to function adequately. The clinicians in the ICU adjust the various ventilator settings in order to achieve a reasonable level of oxygenation and a safe level of carbon dioxide in the blood. The clinicians make these decisions based upon their knowledge of the pathophysiology of the lungs, and of the patient's condition and past medical history.

Attempts have been made to develop advisory systems for intensive care ventilators since the early 70's. However, not many were used clinically. Early systems used an algorithmic approach [Menn et al., 1973]. They were inflexible and they could not keep up with the advances in respiratory intensive care.

Over the years, there have been great advances in ventilatory therapy. A number of ventilatory modes have been developed in the past 30 years. Ventilators have also become more sophisticated. In the 80's and 90's, researchers started to apply artificial intelligence to this increasingly complicated problem [Dojat et al., 1997; Miller PL, 1985; Shahsavar et al., 1995]. With the successful use of fuzzy logic in industrial applications, in the 90's, some researchers have also started to develop intelligent advisory systems based on fuzzy logic for intensive care ventilators [Nemoto et al., 1999; Schuh et al., 2000]. However, only a few of these advisory systems are currently in-use. They include NeoGanesh [Dojat et al., 1997] and FuzzyKBWean [Schuh et al., 2000]. These two systems mainly focus on the weaning phase of the artificial ventilation. The authors are developing a hybrid knowledge-and-model-based advisory system to help clinicians in the maintenance phase of the artificial ventilation. The paper presents how a patient simulator was used for knowledge acquisition in the

development of the knowledge-based module of the system.

1.1. Architecture of the system

The advisory system will generate advice on 4 ventilator settings: the inspired fraction of oxygen (FiO_2), the postivie end-expiratory pressure (PEEP), the inspiratory pressure (PINSP) and the ventilatory rate. The architecture of the system is shown in figure 1. It is divided into two main parts: the top-level knowledge-based module and a lower-level model-based module. Each module is divided into a FiO_2/PEEP subunit which controls the oxygenation-related settings and a PINSP/Ventilatory rate subunit which controls the settings related to the minute ventilation. The top-level module will suggest the types of ventilator settings to be changed and the target arterial partial pressure of oxygen (PaO_2) and arterial partial pressure of carbon dioxide ($PaCO_2$). The lower-level module will derive the amount of change required in each setting.

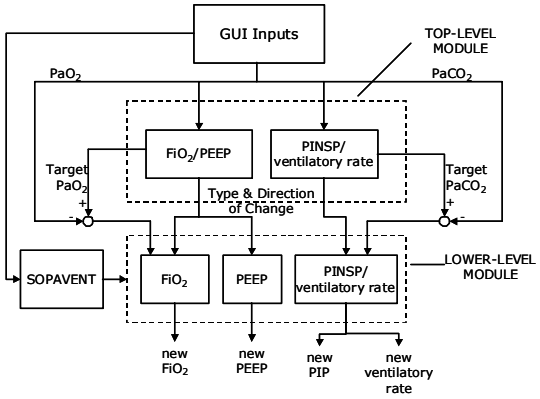

Figure 1. Architecture of the advisory system

This paper presents the knowledge acquisition for the top-level module. The top-level module is implemented in four fuzzy rule-bases. There are two subunits of the top-level module and therefore, two fuzzy rule-bases were derived. The input variables were decided via consultation of the intensive care consultants. For the ventilator settings primarily affect the oxygenation of the patient, i.e. FiO_2 and PEEP, the input variables include the past and present PaO_2, past and present FiO_2, and the PEEP. For the PINSP and ventilatory rate, the input variables include past and present pH, past and present $PaCO_2$, the PINSP and the ventilatory rate. In order to reduce the number of rules, the input variables were not directly input to the fuzzy inference system but first grouped into three variables. For the FiO_2 and PEEP control, the inputs to the fuzzy inference system include the PaO_2, the patient's condition and the support level. The patient's condition is derived from the change in the hypoxemia index (PaO_2/FiO_2) and the support level is derived from the FiO_2 and PEEP.

For the PINSP and the ventilatory rate, the inputs to the fuzzy inference system include the previous $PaCO_2$, the metabolic status and the support level. The metabolic status includes 5 categories: metabolic acidosis, respiratory acidosis, normal, metabolic alkalosis, and respiratory alkalosis. These are derived from the pH and $PaCO_2$ level. The support level is derived from the PINSP and the ventilatory rate.

The structure of the fuzzy inference systems is shown in figure 2. Grid-partitions were used for the fuzzy rule-antecedents, and 'multiplication' was chosen as the inference method. There are three output members for each ventilator setting: reduce, maintain or increase. The output member with the maximum membership value is chosen as the output.

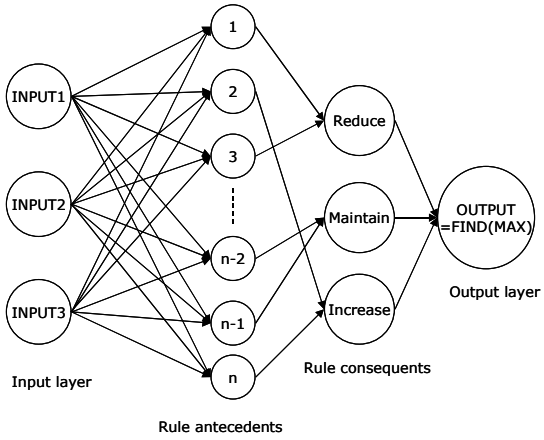

Figure 2. The fuzzy inference system used in the top-level module

1.2. Knowledge acquisition

Most of the medical advisory systems have been developed after extensive literature search and multiple interviews with the domain experts. This is a time-consuming process. In the field of ventilator management, there is often a lack of knowledge, while opinions often differ among experts. Moreover, during interviews, due to the complexity of the problems, an expert will often advise the system to take into consideration all the available data, both qualitative and quantitative. This could result in a system which needs too much computing power to be efficient for clinical use. In addition, the clinicians'

way of analysing the problem often involves a certain heuristic element, therefore, direct translation of their rules into the system may result in a system which is difficult to debug. As the domain experts are often busy in their clinical duties, it is very difficult for them to allocate time for the interviews. For example, to ask one of them to define fuzzy sets for the input variables may take one hour. The more input variables there are, the more rules one has to consider and the more time it takes. It is unnatural for the clinicians to think of the shape of the fuzzy membership functions. It is also unnatural for them to derive a decision based on the fuzzy definitions of the input variables. They make judgements by recognizing patterns and prior knowledge based on experience. To save their time in the knowledge-acquisition process and to improve objectivity, an observational approach using a patient simulator was adopted. Using this approach, the rule-bases were not derived by interviewing experts but were derived by observing how they make decisions and change the ventilator settings in the simulation environment.

2. SIMULATOR DEVELOPMENT

2.1. Model development

The simulator was based upon a process model of patients on artificial ventilation (SOPAVENT), which was developed to provide simulated closed-loop validation of a prototype expert system [Goode, 2000]. The model represents the exchange of O_2 and CO_2 in the lungs and tissues together with their transport through the circulatory system The model was chosen to be physiologically interpretable, yet simple enough so that most of its parameters could be matched to those routinely recorded in the ICU.

The model used a compartmental structure similar to that described in earlier work [Dickinson, 1977], where the circulatory system is represented by lumped arterial, tissue, venous and pulmonary compartments, see figure 3. The lung is sub-divided into three further compartments representing the classic model of pulmonary gas exchange [Riley & Cournard, 1949].

This describes the lung in terms of three lumped functional areas: (1) an *ideal alveolus*, where all gas exchange takes place with a perfusion-diffusion ratio of unity, (2) a *dead space* representing lung areas that are ventilated but not perfused, and (3) a *shunt* that is a fraction of cardiac output, representing both anatomical shunts and lung areas that are perfused but not ventilated.

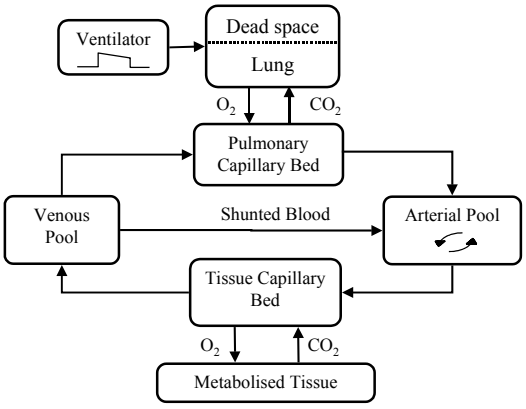

Figure 3. Schematic overview of the patient model

The mass transport of O_2 was described by the following 5 linked differential equations [Thomsen *et al*, 1989];

$$\frac{\partial CaO_2}{\partial t} \cdot Va = \dot{Q}_t \cdot \left[X \cdot CvO_2 + (1-X) \cdot CpO_2 - CaO_2\right] \quad (1)$$

$$\frac{\partial CtO_2}{\partial t} \cdot Vt = \dot{Q}_t \cdot \left[CaO_2 - CtO_2\right] - \dot{V}_{O_2} \quad (2)$$

$$\frac{\partial CvO_2}{\partial t} \cdot Vv = \dot{Q}_t \cdot \left[CtO_2 - CvO_2\right] \quad (3)$$

$$\frac{\partial CpO_2}{\partial t} \cdot Vp = \dot{Q}_t \cdot (1-X) \cdot \left[(CvO_2 - CpO_2) + O_2 Diff\right] \quad (4)$$

$$\frac{\partial C_AO_2}{\partial t} \cdot V_A = RR \cdot (V_T - V_D) \cdot (F_IO_2 - C_AO_2/1000) - \dot{Q}_t \cdot (1-X) \cdot O_2 Diff \quad (5)$$

where

Vx	Where x = A, a, t, v, p - Volumes of alveolar, arterial, tissue, venous, and pulmonary compartments respectively (litres)
$\dot{Q}_t$	Cardiac output (ml blood/min)
X	Fraction of blood shunted past lungs
$\dot{V}_{O_2}$	O_2 consumption by tissues (ml O_2/min, BTPS)
V_D	Alveolar dead-space volume (ml, BTPS)
V_T	Tidal volume (ml, BTPS)
RR	Respiratory rate (breath / min)
C_AO_2	Alveolar O_2 content (ml O_2/l gas)
CxO_2	Where x = a, t, v, p - arterial, tissue, venous and pulmonary O_2 content, respectively (ml O_2/l blood)
t	Time (min)
F_IO_2	Inspired O_2 gas fraction

Equation 1 describes the mixing of de-oxygenated venous blood, shunted past the lungs, and the oxygenated end-capillary pulmonary blood (i.e. non-shunted blood). This mixed arterial blood then passes to the tissue bed (equation 2) where O_2 is utilized by metabolized tissues. The de-oxygenated blood then returns to the pulmonary capillaries via the venous pool (equation 3), which simply behaves as an exponential delay. The O_2 content in the end-capillary pulmonary blood (equation 4) depends upon the rate of O_2 diffusing from the ideal alveolus. Similarly, the O_2 content in the alveolar space depends upon the uptake of O_2 by the pulmonary capillaries and the fresh gas delivered by the ventilator (equation 5). Ventilation is represented as a continuous process to help simplify the model.

The gas exchange between the ideal alveolus and the pulmonary compartment is driven by the O_2 pressure gradient across the diffusion boundary for each gas;

$$O_2Diff = BO_2 \cdot (PB \cdot (CAO_2 / 1000) - PpO_2) \quad (6)$$

where

PpO_2 Pulmonary partial pressure of O_2 (kPa)

PB Barometric pressure (kPa)

and BO_2 is the diffusion coefficient expressed in terms of ml O_2/kPa/l blood and is derived from the O_2 diffusion capacity of the lung (DO_2 in ml/min/kPa) and the non-shunted blood flow rate in l/min;

$$BO_2 = \frac{DO_2}{\dot{Q}_t(1 - X)} \text{ [ml } O_2\text{/kPa/l blood]} \quad (8)$$

Whilst only equations pertaining to the diffusion and circulation of O_2 are presented here, there exists within the model a set of similar equations for CO_2.

In order for the lung diffusion and mass transport equations to work together the O_2 content in the pulmonary compartment, needs to be converted into O_2 partial pressure (PO_2) so that diffusion into the alveolus can be resolved. The nonlinear relationship between the O_2 content and the PO_2 is determined by the haemoglobin binding of O_2, known as the O_2 dissociation curve (ODC), together with a small amount of dissolved O_2 in the blood plasma;

$$C(o_2) = \beta_h \cdot Hb \cdot So_2 + \alpha_o \cdot PO_2 \text{ [ml/l blood]} \quad (9)$$

where

β_h Haemoglobin O_2 binding capacity (ml/g)

Hb Haemoglobin content (g/l)

α_o Coefficient of O_2 dissolved in plasma (ml/l/kPa)

So_2 Oxyhaemoglobin saturation fraction being a function of PO_2, pH, temperature and CO_2 partial pressure (PCO_2).

SOPAVENT uses the ODC described by Kelman (1966). Unfortunately explicit functions to derive PO_2 from O_2 content that allow for shifts in pH and temperature do not exist. Consequently the inverse of the ODC had to be calculated using an iterative secant searching algorithm;

$$PpO_2 = f_{inv}(CpO_2) \quad (10)$$

A similar algorithm for the calculation of the CO_2 content from the PCO_2 (CODC) [Kelman, 1967], was required to derive the CO_2 gas exchange. This function is affected by pH, temperature, haematocrit and SO_2. The co-dependence of the CODC on SO_2 and the ODC on PCO_2 links the O_2 and CO_2 transport systems together.

pH is itself affected by PCO_2 as defined by the Henderson-Hasselbalch equation;

$$pH = pK + log\frac{[HCO_3^-]}{\alpha_c \cdot PCO_2} \quad (11)$$

where

pK Logarithm of the apparent first dissociation constant of carbonic acid, variable with pH and temperature

α_c Coefficient of CO_2 dissolved in plasma (mmol/l/kPa)

$[HCO_3^-]$ Sodium bicarbonate concentration (mmol/l)

It was therefore necessary to resolve pH using the latest PCO_2 estimate before computing the ODC and CODCs.

The inputs to the model are the ventilator settings and the outputs are the arterial and venous PO_2 and PCO_2, and pH. These are computed from the arterial and venous compartment blood gas contents using the inverse ODC and CODCs.

The model was implemented using SIMULINK and MATLAB and clinically tested using data collected from the ICU. Its output matched the actual patient changes in arterial blood gas in response to step disturbances in ventilator settings.

2.2. Construction of the patient scenarios

The simulated patients were constructed based on the data from 11 patients in the ICU of the Royal Hallamshire Hospital, Sheffield, UK. Since the SOPAVENT model required knowledge of the cardiac output and oxygen consumption, only data from patients who were ventilated and had a pulmonary arterial catheter inserted were suitable for the construction of simulated patients. The records in the PDMS between December 1999 and June 2000 were searched and 11 patients were identified. For each patient, there were between 7 and 44 sets of data available for the construction of the simulated events. This data provided 11 simulated patients, one of which was used as a test case so that the user could familiarise himself/herself with the simulator before running the actual simulations.

The patient's demographic data (includes the gender, age, weight and height), ventilator settings, cardiac output, haemoglobin, blood pressures, oxygen consumption, carbon dioxide production, pH, bicarbonate, shunt and deadspace were used to characterise each simulated event. The carbon dioxide production was often not measured. Therefore, it was necessary to estimate it using the oxygen consumption and the respiratory quotient (assumed to be 0.8). The deadspace and the shunt at each simulated event were calculated based on the patient's blood gases, ventilator settings, oxygen consumption, carbon dioxide production and cardiac output using the secant method on the SOPAVENT model.

2.3. Graphic user interface

A GUI (figure 4) was implemented in the MATLAB/SIMULINK environment. This enabled the user to observe the demographic data, the ventilator settings, the blood gases, the blood pressures, the heart rate, the cardiac output, the oxygen consumption, the carbon dioxide production, the haemoglobin level and the body temperature of the current simulated event, see figure 2. It also provided a graphical display of the PaO_2, $PaCO_2$, FiO_2, PEEP and PIP trends. The user can give advice as to the desirable range of the PaO_2, $PaCO_2$, pH and tidal volume. He/she can change the ventilator settings (including FiO_2, PEEP, PIP, ventilatory rate and the inspiratory to expiratory ratio (I:E ratio)) based upon the evidence presented. He/she can also choose from a range of other non-ventilatory advice from the pull-down menu. This advice includes the administration of bicarbonate, initiation of continuous venous-venous haemodialysis, prone ventilation, and blood transfusion.

Figure 4. The graphic user interface for the simulator

3. THE SIMULATIONS

3.1. Simulation procedure

The simulation procedure is shown in figure 5. Four intensive care consultants from the Royal Hallamshire Hospital were invited to undertake the study. Before the simulations, the procedure was explained to the clinician. Then he/she had an opportunity to familiarize himself/herself with the GUI using the test case. Afterwards, the clinician was presented with the first set of data relative to one of the simulated patients. The derived parameters were not shown on the GUI. Only the data directly retrieved from the PDMS was shown. The clinician was asked to key in the target range of PaO_2, $PaCO_2$, pH and tidal volume that he/she felt appropriate for the simulated patient. Then the clinician would need to key in the advised new ventilator settings.

From the advice given by the clinician and the internal parameters of the patient, the simulator calculated the predicted blood gases, and the resulting blood gases were shown to the clinician.

After the clinician was shown the resulting blood gases, the simulator would calculate the blood gases of the next case event based upon the advised ventilator settings and the internal parameters of the new case event. Then the screen was updated using the data, the advised ventilated settings and the calculated blood gases of the new case event.

The clinician was asked to repeat the exercise again until the clinician had completed the simulation on all the case events of the simulated patient. Then he/she could move on to the next simulated patient.

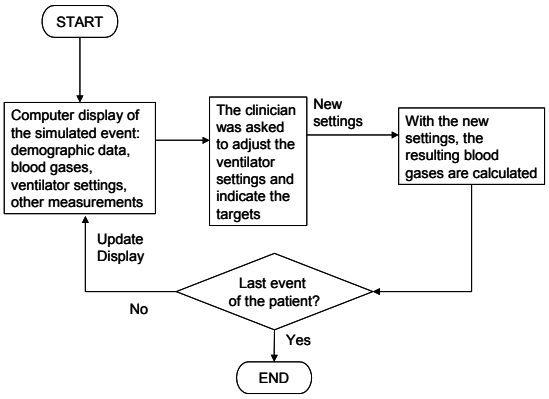

Figure 5. The simulation procedure

3.2. Simulation results

The four intensive care consultants completed a total of 32 simulations. Two consultants completed all 10 simulated patients, one consultant completed 8 simulated patients, and one consultant completed 4 simulated patients. Two of the consultants did not finish all 10 simulated patients because of time constraints and unexpected personal circumstances. These resulted in a total of 788 simulated events to be used to derive the input fuzzy partitions and fuzzy rule-bases.

4. DEVELOPMENT OF THE FUZZY RULE-BASES

4.1. Methodology

The targets set by the clinicians were used in the derivation of the parameters for the input fuzzy sets for the four input variables: PaO_2, $PaCO_2$, pH and the tidal volume. The tidal volume was normalised to the body weight of the patient. The input space for each of the input variables was divided into three fuzzy partitions: low, normal and high. The cumulative distributions of the target range set by the clinicians were used to derive the parameters for the fuzzy membership function. The derivation was based on the assumption that the fuzzy membership value represents the probability that an input will be classified as belonging to the respective fuzzy set by an intensive care consultant. For example, figure 6 shows the histogram and the cumulative frequency for the upper limit of the acceptable tidal volume level set by the consultants. From the cumulative frequency curve, one could deduce that if the tidal volume was more than 11.5 ml/kg, all of the consultants would regard it to be too high and therefore, it should be regarded as high and it will be assigned a fuzzy membership value of 1 in the fuzzy set 'high' and 0 in fuzzy set 'normal'. Therefore, from the cumulative frequency distribution of the upper and lower limits, one could derive the fuzzy membership values.

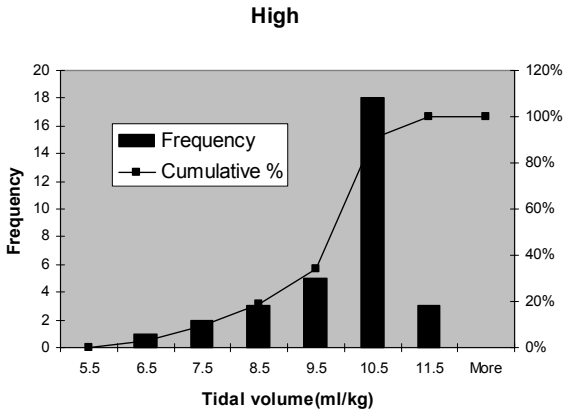

Figure 6. The histogram and cumulative frequency of the upper limit of tidal volume set by the clinicians

Sigmoidal membership functions were used for the fuzzy sets 'low' and 'high' whereas bell-shaped membership functions were used for the fuzzy sets 'normal'. The sigmoidal membership function is given by:

$$\mu(x) = 1/(1+\exp(-a\cdot(x-c))) \qquad (11)$$

where x is the value of the input, μ(x) is the membership value, a and c are the parameters. The bell-shaped membership function is defined by:

$$\mu(x) = 1/((1+abs(x-c)/a).\hat{}\,(2b)) \qquad (12)$$

where x is the value of the input, μ(x) is the membership value, a, b and c are the parameters. The parameters of the fuzzy sets were derived using the experimental data and calculated using the non-linear least squares programme provided by the MATLAB statistics toolbox.

The fuzzy rule-base was derived from the experimental data resulting from the simulations. Each simulated event constituted one data set. The derivation of the initial fuzzy rule-base was based on the statistical analysis of the data from the simulation. From the simulation of each case event, the degrees of membership in the rule-antecedents were calculated. The clinicians' advice in each ventilator settings for the associated case event was considered the target output of the fuzzy rule-bases.

During the analysis, each set of data consisted of the degree of membership in a rule-antecedent and the advice on the ventilator setting (reduce, maintain or increase). Therefore, for each rule-antecedent, there existed a collection of the degree of membership and advised outputs. The range of the degree of membership for each rule-antecedent was divided into 10 intervals. The frequency of each category of the consultants' advice in each degree of membership interval was derived. If a rule-antecedent should result in a particular advice being given, one should find a positive correlation between the probability (the relative frequency) of the advice being given and the degree of membership. Hence, the output (rule-consequent) associated with a rule-antecedent was determined using correlation analysis.

Not all the fuzzy rules could be derived from the correlation analysis because some of the results were equivocal. Therefore, an intensive care consultant was asked to review the initial rule-base and to supplement it where necessary.

4.2. Results

4.2.1 Input fuzzy sets

The fuzzy partitions derived for the primary input variables PaO_2, $PaCO_2$ and pH are shown in figure 7 to figure 9. The secondary inputs include the patient's condition and the ventilatory support level for the FiO_2/PEEP subunit, and the acid-base status and the ventilatory support level for the PINSP/Ventilatory rate subunit.

For the FiO_2/PEEP subunit, the patient's condition is determined by the percentage change in the hypoxaemia index (PaO_2/FiO_2). Its fuzzy partitions were derived from the probability distribution of the percentage change in the hypoxaemia index among the simulated patients. The fuzzy partitions are shown in figure 10.

The ventilatory support level is determined by the FiO_2 and PEEP levels. The therapeutic range of FiO_2 was found to vary between 0.25 to 1 and the therapeutic range of PEEP varied from 0 to 20 cmH_2O. Both the FiO_2 and PEEP were normalized to the range [0,1]. Five cluster centres were defined as shown in Table 1.

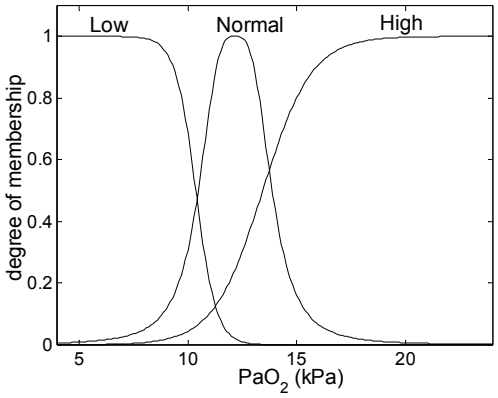

Figure 7. The fuzzy partitions for PaO_2

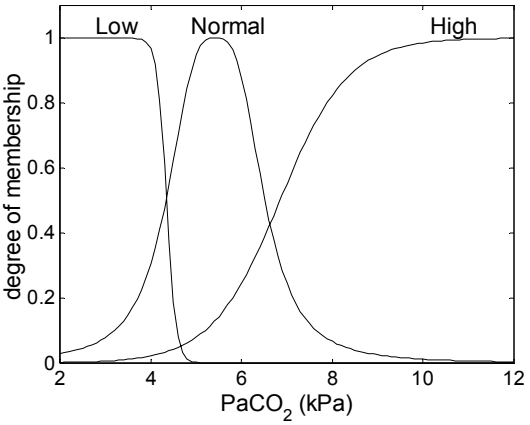

Figure 8. The fuzzy partitions for $PaCO_2$

The degree of membership in each ventilatory support category for a particular set of inputs were determined by the Euclidean distance between the normalized input FiO_2 and PEEP levels, and the cluster centres. Arbitrarily, a degree of membership of 0.5 was assigned to any data point at a distance of 0.25 from the cluster centre. That gives a membership function of

$$\mu_c(x) = \exp(-\frac{\|x-c\|^2}{0.1803}) \qquad (13)$$

where $\mu_c(x)$ is the membership of x in cluster c, x = [normalized FiO_2, normalized PEEP] and $\|x-c\|$ is the Euclidean distance of x from the cluster centre c.

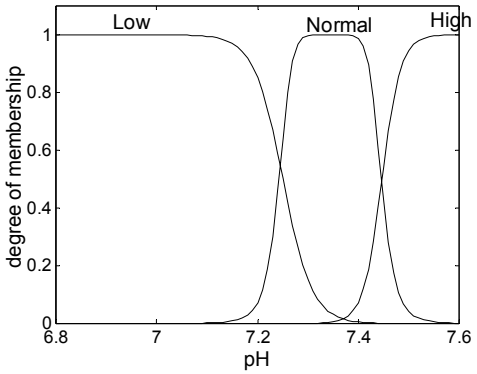

Figure 9. The fuzzy partitions of pH.

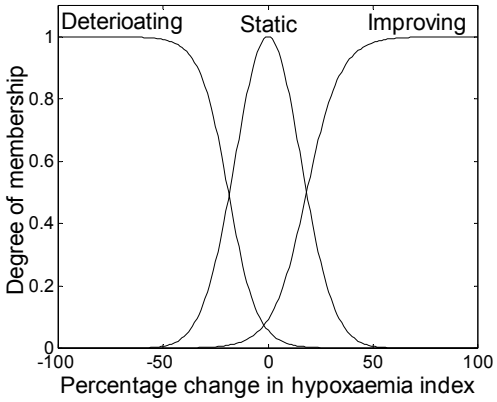

Figure 10. The fuzzy partitions for the patient's condition in the FiO_2/PEEP subunit

Support Level	Cluster Centre
minimal	0, 0
moderate with PEEP dominance	0.25, 0.75
moderate	0.5, 0.5
moderate with FiO_2 dominance	0.75, 0.25
maximal	1, 1

Table 1. The fuzzy cluster centers of the support levels in the FiO_2/PEEP subunit

For the PINSP/Ventilatory rate subunit, the metabolic status is derived from the pH and $PaCO_2$ as defined in Table 2. The 'multiplication' was used as the 'And' method. The ventilatory support level was derived from the normalized PINSP and the Ventilatory rate in a similar way to that of the oxygen-related ventilator settings FiO_2 and PEEP. The therapeutic range of the PINSP is from 10 to 40 cmH_2O and that of the Ventilatory rate is from 4 rpm to 20 rpm. Both the PINSP and the Ventilatory rate were normalized to [0,1] and the cluster centre for each fuzzy member was defined as indicated in Table 3. The fuzzy membership of an input x = [normalized PINSP, normalized Ventilatory rate] is given by equation. 13.

Metabolic status	pH	$PaCO_2$
metabolic acidosis	low	low
respiratory acidosis	low	high
normal	normal	normal
metabolic alkalosis	high	high
respiratory alkalosis	high	low

Table 2. The definitions for the metabolic status.

Support Level	Cluster Centre
minimal	0, 0
moderate with Ventilatory rate dominance	0.25, 0.75
moderate	0.5, 0.5
moderate with PINSP dominance	0.75, 0.25
maximal	1, 1

Table 3. The cluster centers defined for the support level of the PINSP/Ventilatory rate subunit

4.2.2 Fuzzy rule-bases

The grid partition was used for the fuzzy rule-based system. There are 45 rules in each of the FiO_2 and PEEP rule-bases and 75 rules in each of the PINSP and Ventilatory rate rule-bases. The rule-consequent of 6 FiO_2 rules, 7 PEEP rules, 27 PINSP rules, and 28 Ventilatory rate rules could not be decided due to a lack of statistical significance. For the undetermined rules, possible consequents were determined by ruling out those with significantly negative correlation coefficients. The candidate consequents of these rules were then presented to the intensive care consultant for the final verdict. The fuzzy rule-bases for the four ventilator settings are shown in to in the Appendix.

5. VALIDATION

The rule-bases were validated with the simulation data and retrospective clinical data. The retrospective clinical data were collected from the PDMS of the ICU. Ten ventilated patients were randomly chosen from the database. For each patient, the blood gas records from the time when artificial ventilation began to the time when the weaning process started were retrieved. Due to the retrospective nature of the data collection, it was

not always clear-cut when the weaning process started. After discussions with the intensive care consultant, it was decided that it would be defined as the time when the ventilatory mode was changed from BiPAP to CPAP/ASB/IPPV because that usually indicated that the clinicians intended to wean the patient. The ventilator settings (FiO_2, PEEP, PINSP and Ventilatory rate) when the blood gas was taken were recorded. The ventilator settings in the last set of blood gas were also recorded. These provided data for the input to the fuzzy rule-bases. For the FiO_2 and PEEP rule-bases, each set of inputs consisted of the current PaO_2, the last PaO_2, FiO_2, the last FiO_2 and PEEP. For the PINSP/Ventilatory rate rule-bases, the current $PaCO_2$, the pH, the last $PaCO_2$, the PINSP and Ventilatory rate formed the input data. The patient record in the one-hour following each blood gas result was examined to look for any changes in the ventilator settings.

The changes in ventilator settings recorded in the PDMS were compared to the fuzzy rule-bases outputs. Three grades of matching were defined: 1: an exact match was defined when the change recorded in the PDMS matched exactly with the fuzzy rule-base output, 2: a partial match was defined when the PDMS record differed from the fuzzy rule-base output but the two were not in opposite direction (e.g. an increase in the setting in the PDMS record and an unchanged was advised by the fuzzy rule-base), 3: a conflict was defined when the two were in opposite directions.

	exact match	partial match	conflict
FiO_2	119 (78.8%)	32 (21.2%)	0 (0.0%)
PEEP	107 (70.9%)	44 (29.1%)	0 (0.0%)
PINSP	49 (32.5%)	99 (65.6%)	3 (2.0%)
Ventilatory rate	123 (81.5%)	24 (15.9%)	1 (0.7%)

Table 4. The distribution of the exact matches, partial matches and conflicts between the fuzzy rule-base outputs and the PDMS records for each of the four ventilator settings. The total number of cases was 151.

One hundred and fifty one data sets were available for the validation of the system. Table 4 shows the distribution of the exact matches, partial matches and conflicts for each of the ventilator settings. It can be seen that the performance of the FiO_2, PEEP and Ventilatory rate rule-bases were good. The proportion of exact matches was over 70%, whereas the PINSP rule-base performed badly, with only 32.5% exact matches.

6. DISCUSSION

A knowledge-based module for generating qualitative advice for clinicians on four ventilator settings (FiO2, PEEP, PINSP and Ventilatory rate) has been developed. The knowledge acquisition was achieved using an observational approach based on a patient simulator. The use of a simulator to learn how the clinicians deal with various clinical situations speeds up the knowledge acquisition process in the construction of an expert system. In this study, the average time taken by a clinician to complete the simulation on three patients was ½ hour. This is much less than an average interview during the knowledge acquisition process. This also enabled the system to 'learn' from a few clinical experts on similar scenarios.

Each subunit of the module was implemented via a fuzzy rule-base. The parameters of the input membership functions and the rules were derived after statistical analysis of the data collected from the simulation study. In order to reduce the number of rules, some of the primary input variables were summarized into secondary input variables via clustering. One drawback is that the simulation environment can never be the same as the real ICU environment. Therefore, the rule-bases derived using the simulator had to be validated against data from the ICU.

The validation showed that the FiO_2, PEEP and Ventilatory rate rule-bases matched the clinicians' actions recorded in the PDMS to a high degree whereas the PINSP rule-base matched the clinicians' actions in only 32.5% of the cases. One possible reason is that there might be a difference between the simulation environment and the actual clinical environment. However, if this is the case, why were the FiO_2, PEEP and Ventilatory rate rule-bases not affected to the same extent? One possible reason is that the PINSP is the setting that is often used to control the $PaCO_2$ but the adjustment of the $PaCO_2$ very often depends on the acid-base balance of the patient. In the actual clinical environment, the physician can manage the acid-base status of the patient using metabolic means, for example, by prescribing bicarbonate infusions or haemodialysis. Although in the patient simulator the clinicians were allowed to suggest therapeutic procedures such as haemodialysis, these procedures were not carried out in the simulated patients here. Some clinicians might therefore try to manage the acid-base status solely by using ventilation manoeuvres. However, this does not explain why Ventilatory rate rule-base performed significantly better than the PINSP rule-base as both are used to control $PaCO_2$.

The fuzzy rule-bases derived can be tuned using artificial intelligence techniques based on neural networks or genetic algorithms, although the latter are more time-consuming to develop. In order to improve performance, the tuning can be done using retrospective clinical data from the PDMS as training data.

7. CONCLUSION

A patient simulator has been used for knowledge acquisition from the clinicians on ventilator management in the ICU. The input fuzzy partitions and the fuzzy rules were derived after statistical analysis of the simulation data. The FiO_2, PEEP and Ventilatory rate rule-base were shown to match the clinicians' actions to a high degree but the PINSP rule-base matched the clinicians' actions in only 32.5% of cases. Therefore, the PINSP rule-base has to be refined in the future. Nevertheless, the use of simulation in knowledge acquisition has speeded up the knowledge acquisition process and it provided the means to observe how different clinicians manage the ventilator under the same scenario.

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APPENDIX

Table A- 1. The FiO_2 rule-base

When the PaO_2 is low	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	increase	increase	maintain
moderate (PEEP dominant)	increase	increase	maintain
moderate	increase	increase	maintain
moderate (FiO_2 dominant)	increase	increase	maintain
maximal	increase	increase	increase

When the PaO_2 is normal	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	maintain	maintain	maintain
moderate (PEEP dominant)	increase	maintain	maintain
moderate	maintain	maintain	maintain
moderate (FiO_2 dominant)	increase	maintain	maintain
maximal	increase	maintain	reduce

When the PaO_2 is high	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	maintain	maintain	reduce
moderate (PEEP dominant)	maintain	reduce	reduce
moderate	maintain	reduce	reduce
moderate (FiO_2 dominant)	maintain	reduce	reduce
maximal	reduce	reduce	reduce

Table A- 3. The PEEP rule-base

When the PaO_2 is low	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	increase	increase	increase
moderate (PEEP dominant)	increase	increase	increase
moderate	increase	increase	maintain
moderate (FiO_2 dominant)	increase	increase	increase
maximal	increase	increase	increase

When the PaO_2 is normal	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	maintain	maintain	maintain
moderate (PEEP dominant)	increase	maintain	reduce
moderate	increase	increase	reduce
moderate (FiO_2 dominant)	increase	increase	reduce
maximal	maintain	increase	reduce

When the PaO_2 is high	Condition		
Support	**deteriorating**	**static**	**improving**
minimal	maintain	maintain	maintain
moderate (PEEP dominant)	maintain	reduce	reduce
moderate	maintain	maintain	reduce
moderate (FiO_2 dominant)	maintain	maintain	maintain
maximal	maintain	maintain	maintain

Table A- 5. The PINSP rule-base

When the past $PaCO_2$ is low	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	maintain	increase	maintain	reduce	reduce
Moderate support (PINSP dominant)	maintain	increase	reduce	reduce	reduce
Moderate support	increase	increase	maintain	reduce	reduce
Moderate support (Ventilatory rate dominant)	increase	increase	maintain	reduce	reduce
Maximal support	maintain	maintain	reduce	reduce	reduce

When the past PaCO2 is normal	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	maintain	increase	maintain	reduce	reduce
Moderate support (PINSP dominant)	maintain	increase	reduce	reduce	reduce
Moderate support	increase	increase	maintain	reduce	reduce
Moderate support (Ventilatory rate dominant)	maintain	increase	maintain	reduce	reduce
Maximal support	maintain	increase	reduce	reduce	reduce

When the past PaCO2 is high	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	increase	increase	maintain	maintain	reduce
Moderate support (PINSP dominant)	maintain	increase	reduce	reduce	reduce
Moderate support	increase	increase	maintain	reduce	reduce
Moderate support (Ventilatory rate dominant)	increase	increase	maintain	reduce	maintain
Maximal support	maintain	maintain	reduce	reduce	reduce

Table A- 7. The Ventilatory rate rule-base

When the past $PaCO_2$ is low	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	increase	increase	maintain	reduce	reduce
Moderate support (PINSP dominant)	maintain	increase	maintain	reduce	maintain
Moderate support	maintain	increase	maintain	reduce	reduce
Moderate support (Ventilatory rate dominant)	maintain	increase	maintain	reduce	reduce
Maximal support	maintain	maintain	maintain	maintain	reduce

When the past PaCO2 is normal	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	maintain	increase	maintain	reduce	reduce
Moderate support (PINSP dominant)	increase	increase	maintain	maintain	reduce
Moderate support	increase	increase	maintain	maintain	reduce
Moderate support (Ventilatory rate dominant)	maintain	increase	maintain	maintain	reduce
Maximal support	maintain	increase	reduce	reduce	reduce

When the past PaCO2 is high	Metabolic acidosis	Respiratory acidosis	Normal	Metabolic alkalosis	Respiratory alkalosis
Minimal support	maintain	increase	maintain	maintain	maintain
Moderate support (PINSP dominant)	increase	increase	maintain	maintain	reduce
Moderate support	maintain	increase	maintain	reduce	reduce
Moderate support (Ventilatory rate dominant)	maintain	maintain	maintain	reduce	reduce
Maximal support	maintain	maintain	maintain	reduce	reduce