An adaptive controller for noisy pressure controlled ventilation

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Abstract— **There is a growing interest in the use of variable ventilation and pressure controlled ventilation (PCV). However, the combination of these approaches as "noisy PCV" would require a mechanical ventilation system that adapts to the respiratory system mechanics. In this work, we evaluated a new control system based on an adaptive least mean squares approach, which automatically tunes the pattern of the driving pressure during PCV to achieve a desired variability pattern of tidal volume (VT). The controller was tested during numerical simulations, applying step changes in respiratory system mechanics and in mechanical ventilation settings. The time needed to converge (t_c) to the desired VT variability pattern after each change, and the difference in minute ventilation (ΔMV) between measured and target pattern of VT during t_c were determined. The numerical simulations of the new controller resulted in: 1) $t_c < 30$ respiratory cycles, except when underestimation of the apparent elastance of the respiratory system (E^*) was > 25 %; 2) t_c only minimally influenced by E^*; 3) larger t_c when E^* was not correctly estimated; 4) absolute value of ΔMV < 22.2 %. The new noisy PCV controller had a satisfactory performance and could prove interesting for mechanical ventilation practice.**

Keywords— **mechanical ventilator, biologically variable ventilation, adaptive least mean squares, acute lung injury.**

I. INTRODUCTION

Experimental studies in models of acute lung injury (ALI) showed that variable mechanical ventilation improves arterial oxygenation, intrapulmonary shunt, elastance of the pulmonary system [1,2] and even reduces lung histological damage [3] when compared to conventional non-variable mechanical ventilation modes. Currently, variable controlled mechanical ventilation is usually performed as a modification of the conventional volume controlled ventilation (VCV), with the tidal volume (VT) of every respiratory cycle varying according to a pre-established pattern with desired mean (VT_m) and standard deviation (VT_s) [4]. However, since pressure controlled ventilation (PCV) reduces peak airway pressures and homogenize the distribution of ventilation across the lungs compared to VCV [5,6], there is a growing interest in the use of PCV in patients with ALI. Thus, the combination of variable ventilation with PCV (noisy PCV) could prove useful in clinical practice. Nonetheless, the mechanical properties of the lungs may vary over time [7], modifying the relationship between the driving pressure (Ps) and VT during PCV. Hence, the problem exists of how the breath-to-breath variations in Ps should be determined in order to obtain a noisy PCV where the target VT_m and VT_s are matched and protective low VT is maintained, independently of the mechanical properties of the respiratory system.

The aims of this work are to introduce and to evaluate a novel adaptive control system for noisy PCV capable of automatically and continuously tuning the pattern of Ps in the presence of changes in the lung mechanics to achieve the target VT_m and VT_s.

II. METHODS

A. Control system

Figure 1 illustrates the structure of the control system for noisy PCV.

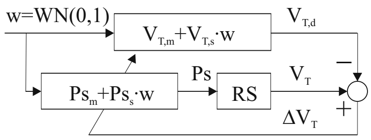

Figure 1 - Schematic diagram of the control system for noisy pressure controlled ventilation (noisy PCV). RS: respiratory system of the subject undergoing noisy PCV.

The input of the control system (w) is a white noise with Gaussian distribution with mean = 0 and variance = 1. Before the beginning of a given respiratory cycle *i* the desired tidal volume for that cycle (VT_d) is computed as shown in (1):

$$VT_d(i)=VT_m+VT_s\cdot w(i) \quad (1)$$

where VT_m and VT_s are respectively the desired mean and standard deviation of the overall distribution of VT, determined *a priori* by the operator. At the same time, the driving pressure Ps to be delivered by the mechanical ventilator is computed as shown in (2):

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$$Ps(i)= Ps_m(i)+Ps_s(i)\cdot w(i) \quad (2)$$

where Ps_m and Ps_s can be interpreted as the mean and the standard deviation of the Ps level. These parameters are updated at every cycle by the control system, in order to reach the desired characteristics of the VT series. At the beginning of each expiration, and after computing the difference ΔVT between VT_d and the measured VT, the new values of Ps_m and Ps_s are computed using a least mean squares (LMS) adaptive method (30) as shown in (3) and (4), respectively:

$$Ps_m(i+1)= Ps_m(i)- \alpha_m(i)\cdot\Delta VT(i) \quad (3)$$

$$Ps_s(i+1)= Ps_s(i)- \alpha_s(i)\cdot\Delta VT(i)\cdot w(i) \quad (4)$$

where α_m and α_s represent adaptation steps (for the mean and for the st.dev., respectively) that are usually constant over time [8]. However, in order to guarantee a good trade-off between the speed and smoothness of convergence to the desired VT pattern in different conditions of the respiratory system, we used adaptation steps values that are a function of estimates of the Ps/VT ratio, hereby named "apparent elastance of the respiratory system" (E^*), as shown in (5), (6, and (7):

$$E^*(i) = \frac{1}{N}\sum_{j=0}^{N}\frac{Ps(i-j)}{VT(i-j)} \quad (5)$$

$$\alpha_m(i)=E^*(i)/2000 \quad (6)$$

$$\alpha_s(i)=0.001/(0.0417+\exp(-0.1034\cdot E^*(i))) \quad (7)$$

where N = 15 (this choice of N was considered a good compromise between accuracy of the estimate and fast response to changes in the estimated parameter). Also, in the first step of the control, Ps_m and Ps_s are initialized as shown in (8) and (9):

$$Ps_m(1)=VT_m\cdot E^*(1) \quad (8)$$

$$Ps_s(1)=VT_s\cdot E^*(1) \quad (9)$$

To avoid Ps values that can worsen lung injury through overdistension, the maximum values of Ps_m, Ps_s and w(i) were limited to 40 cmH_2O, (40 - Ps_m)/2, and 1.0 (absolute value), respectively.

B. Numerical simulations

The numerical simulations were performed with routines written for *Matlab* (*Mathworks*, MA, USA), using a model of the relationship between volume and pressure of the respiratory system according with (10) [9]:

$$P=R\cdot F+E\cdot V+EEP \quad (10)$$

where P is the airway pressure, R is the resistance of the respiratory system, F is the airflow, E is the elastance of the respiratory system, V is the volume, and EEP is the end expiratory pressure. Assuming that during PCV the difference between P and EEP throughout inspiration (i.e. Ps) is constant, VT can be calculated solving (10):

$$VT=V(t_I)=Ps\cdot(1-\exp(-t_I\cdot E/R)/E=Ps/E^* \quad (11)$$

where t_I is the length of inspiration and E^* is the apparent elastance of the respiratory system, which depends nonlinearly on E, R and t_I. Hence, the relationship between the input and output of the control system (Ps and VT, respectively) is linear and depends only on E^*.

The protocol for numerical simulations included different tasks, which are shown in Table 1. Two scenarios were considered for assessing the behaviour of the control system: 1) transition from "conventional" PCV to noisy PCV, i.e. zero to 30 % coefficient of variation in VT. The variability of 30 % was used because it is compatible with what found in healthy humans [10], and was associated with the optimal response in gas exchange and respiratory system mechanics in an animal model of ALI [2]; 2) step increase in E^* of 30 cmH_2O/L, which we considered a plausible "worst case" scenario.

Table 1 – Characteristics of the numerical simulations

Sim. type	Initial condition	Target condition
1	$15\leq E^*(0)\leq 155$, $Ps_s(0)=0$, $Ps_m(0)=15$	$E^*(t)=E^*(0)$ $VT_m=240^{\$}$ $VT_s=72^{\&}$
2	$15\leq E^*(0)\leq 155$ $Ps_m(0)=VT_m\cdot E^*(0)$, $Ps_s(0)=VT_s\cdot E^*(0)$ $VT_m=240^{\$}$, $VT_s=72^{\&}$	$E^*(t)=E^*(0)+30$, $VT_m=240^{\$}$, $VT_s=72^{\&}$

$^{\$}$ 8 ml/kg for a 30 kg animal (experimental model used by our group) [1]; $^{\&}$ 30 % of VT_m. Units: VT_m, VT_s (ml); Ps_m, Ps_s (cmH_2O); E^* (cmH_2O/L).

These simulations were performed for different values of E^* in the range between 15 and 150 cmH_2O/L (with discrete steps of 5 cmH_2O/L), which is compatible with the range of values between healthy and severely injured lungs [11]. Since (6) and (7) for the selection of α_m and α_s rely on estimates of E^*, the simulations were repeated also including errors of ± 25 % and ± 50 % in the estimate to verify the robustness of the noisy PCV control system. For each task in the numerical model, 100 simulations were performed, using each time a different pattern of Gaussian noise w(i) as input of the control system. In each numerical simulation, 1000 iterations corresponding to 1000 respiratory cycles were performed.

C. Performance indexes

For the numerical simulations and bench evaluation the number of respiratory cycles needed for convergence (t_c) was estimated as the last respiratory cycle in the simulation for which the root mean square error (RMSE) between VT_d and VT along the 10 preceding respiratory cycles was

> 10 mL. The control system was arbitrarily considered to be *very fast*, *fast*, *moderately fast* if t_c was situated in the ranges 1 to 24, 25 to 48, and 49 to 72 cycles respectively, or *slow* otherwise. Also, the relative difference in minute ventilation (ΔMV) between measured and target VT pattern in the time needed to convergence was computed. ΔMV was arbitrarily considered to be *small* or *moderate* if its absolute value was in the range 0 to 10 %, or 10 to 20 % respectively, or *high* otherwise

D. Statistics

Values are given as mean, standard deviation (st.dev.) and/or range (for the range "from X to Y" the notation [X Y] will be adopted hereby). For the numerical simulations, the non-parametric Spearman correlation test was used to test the relationship between E^* and t_c or ΔMV, while significance of the differences between the effect of positive/negative and large/small errors in the estimation of E^* was tested using the non-parametric Wilcoxon signed rank test.

III. RESULTS

Figure 2 shows the effects of the error in the estimation of E^* on the mean convergence time of the control system in the numerical simulations, and on the difference in MV during such time compared to the target VT pattern. For the task consisting in switching from conventional to noisy PCV, the control system was *fast* or *very fast* in all simulations (range of t_c = [1 37] cycles, mean 12.2 cycles, st.dev. 6.7 cycles, Figure 2a), accompanied with a *small* or *moderate* transient change in MV (range of ΔMV = [-16.9 7.9] %, mean -1.7 %, st.dev. 5.9 %, Figure 2c), with a very slight but generally significant dependence of ΔMV and t_c on E^* (absolute value of $r < 0.08$ with $p < 0.05$, except for correlation between t_c on E^* for error of 0 and -25 % in E^* estimate, which were not significant). Also, slower convergence and a larger absolute value of ΔMV were found for an absolute error of 50 % when compared to an absolute error of 25 % ($p < 0.001$). Furthermore, for the same absolute error, underestimation of E^* resulted in generally slower convergence than overestimation ($p < 0.001$), and the sign of the error in E^* estimate corresponded to that of ΔMV. For the task consisting in a sudden increase of E^* by 30 cmH_2O/L, the control system was always *fast* or *very fast* (range of t_c = [1 30] cycles, mean 11.7 cycles, st.dev. 2.8 cycles, Figure 2b) and associated with a moderate reduction in MV (range of ΔMV = [-1.1 -14.6] %, mean -3.7 %, st.dev. 2 %, Figure 2d), except for the simulations involving 50 % underestimates of E^*. In this case, the system was still *very fast* on average (mean t_c = 20.6 cycles), but for smaller values of

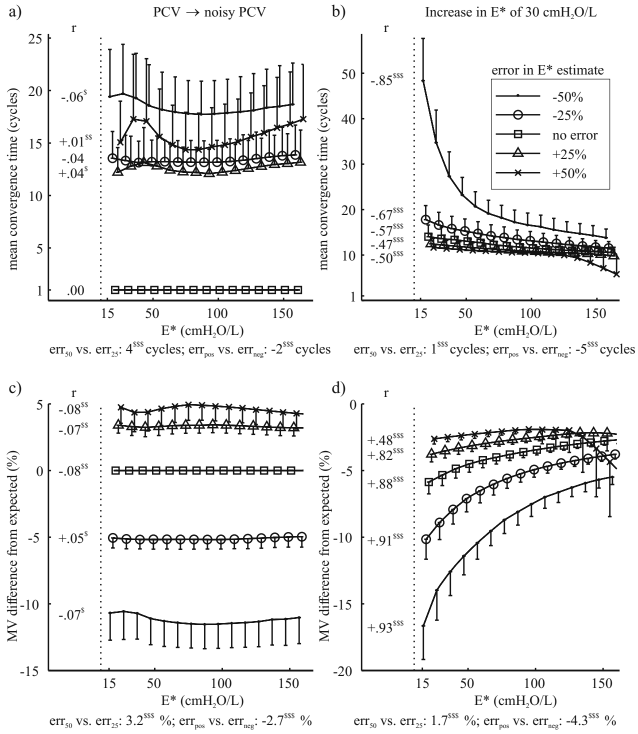

Figure 2 – Mean and standard deviation (vertical bars) of the convergence time and of variation of minute ventilation until convergence, in 100 numerical simulations (6) and (7) for different values of E* and different errors in its estimate: a) and c), transition from conventional PCV to noisy PCV (simulation type 1 in); b) and d) step change in E* (simulation type 2 in Table 1). r: Spearman correlation coefficient with E^*; "err_{50} vs. err_{25}" and "err_{pos} vs. err_{neg}": difference in performance between 50% and 25% absolute error in E^* estimate, and between positive and negative error, respectively (difference between medians of absolute values and p-value of Wilcoxon rank sum test are reported);\$:p<0.05;\$\$:p<0.01; \$\$\$:p<0.001.

E^* it was slower and associated with a somehow greater reduction in MV (for example, for $E^* < 35$ cmH_2O/L mean t_c = 38.7 cycles, range [22 74] cycles, mean ΔMV=-14.6 %, range [-8.4 -22.2] %). The convergence time and the reduction in MV were on average smaller at higher values of E^* ($p < 0.001$), and both were influenced by the error in E^* estimate. In fact, t_c and the absolute value of ΔMV decreased for increasing value of the error ($p < 0.001$, Figure 2b/d), with positive errors resulting in a better performance than negative errors (and than no error, even if the magnitude of differences in this case was very limited, $p < 0.001$, Figure 2b/d).

IV. DISCUSSION

The main findings of this work were that, during numerical simulations, the new adaptive controller for noisy PCV:

1) achieved the desired pattern of variability of VT in less than 30 respiratory cycles, except when underestimation of E^* was > 25 %; 2) had a convergence time that was only minimally influenced by E^*; 3) was slower when E^* was not correctly estimated; 4) led to less than 22.2% difference between measured and target MV until convergence was achieved.

To our knowledge, the controller presented in this work is the first solution to the problem of automatically maintaining a desired variability pattern of VT during PCV. The performance of the noisy PCV control system for both the numerical and electro-mechanical simulations was satisfactory, guaranteeing a convergence of the measured VT pattern to the desired one in a limited number of cycles (< 40). It is worth noting that the conditions simulated in this work posed more difficult challenges to the noisy PCV control algorithm than it is likely to be encountered in the practice of mechanical ventilation. Romero et al. [12] showed that, intravenous administration of methacholine in air-exposed rabbits doubles E after approximately 60 s, with a much smoother transition than the step-change considered in our simulations. Thus, the convergence times reported can be interpreted as very conservative upper bounds for convergence times in possible future practical applications.

Since (6) and (7) of the control system are based of an estimate of E^*, one could question if, in practical applications, the potential improvement in performance resulting from their use can be outbalanced by errors in such estimate. However, errors as high as 50% in the estimation of E^* had only a minor effect on the convergence time, as shown in the numerical simulations.

As expected, changes in E^* and VT_m resulted in differences between the measured and the target MV until convergence of the control algorithm. Both during numerical simulations and tests with the physical model, ΔMV was always less than 22.2 % in absolute value, while mean values were no higher than 15%. Moreover, the higher was the accuracy of the estimation of E^*, the lesser ΔMV was. Theoretically, such transients may result in alterations in the mean airway pressure as well as gas exchange. However, due to its relative short duration, which is equivalent to the convergence times measured, derecruitment or overdistension of lung units, as well as deterioration of oxygenation and CO_2 elimination are unlikely. It should be kept in mind that, under conventional PCV in clinical practice, such transients may last much longer, since manual adjustment of settings of the mechanical ventilator by the medical staff are performed after changes in MV have been detected by the device over several cycles.

V. CONCLUSIONS

The adaptive controller for noisy PCV evaluated in this work has several characteristics that make it attractive for the implementation in future commercial devices and the use in clinical practice. In fact, it is based on few simple equations and only two parameters to be set by the operator (i.e. mean and st.dev. of VT pattern), facilitating its implementation in existing mechanical ventilators without increased computational resources, and making its operation in a clinical routine scenario quite intuitive. Also, the only external inputs affecting the adaptive control steps are V and P, yielding a robust system for most applications. Since the new noisy PCV controller yielded relatively short convergence times and only limited transient variation between desired and target MV, it could prove interesting for mechanical ventilation practice, particularly in patients with acute lung injury.

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