Combining Iterative Absolute EIT, Difference EIT and Control Theory to Optimise Mechanical Ventilation

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Abstract: We examine the combination of absolute and difference imaging to provide fast pseudo-absolute EIT reconstructions required for the recovery of local ventilation parameters. Parameters recovered from simulations are incorporated into an optimal control framework to demonstrate personalised optimisation of mechanical ventilation.

1 Introduction

Methods have been proposed to incorporate patient specific modelling into the automated control of mechanical ventilation through the use of EIT [1]. Through these methods it is possible to generate the H^1 minimal pressure profile to take ordinary differential equation (ODE) model of lungs from given initial state to specified target state while minimising the pressure gradients applied. Two limitations of this method are the requirement for absolute values of conductivity in ODE parameter recovery and the sensitivity of the generated pressure profiles to the target ventilation state.

In this paper we examine possible solutions to these limitations. To address the need for fast estimates of absolute conductivity, we investigate the accuracy of ODE parameters recovered through pseudo-absolute EIT reconstructions [2]. We also propose a framework to produce pressure profiles optimising regional recruitment while minimising gradients of pressure.

2 Pseudo-absolute Reconstruction

Pseudo-absolute EIT reconstruction assumes additional imaging modalities allow a segmented mesh of the thorax to be constructed [3, 4], which is used to perform a very low dimensional absolute reconstruction. The absolute values are then incorporated into the conductivity Jacobian for further difference imaging.

To test this algorithm's utility in automated ventilator control we generate simulated EIT reconstructions by coupling a compartmental ODE lung model to a segmented thorax mesh in EIDORS 3.9 [5]. We then examine the errors in ODE parameter recovery under errors in both mesh segmentation and signal measurement.

3 Optimised Control

The compartmental ODE model used in this paper can be written in the form

$$\dot{\mathbf{y}}(t) = A\mathbf{y}(t) + Bu(t), \tag{1}$$

where $\mathbf{y}(t)$ is a vector containing air volume of each lung compartment at time t, $u(t)$ is the applied pressure at time t, and A and B are matrices constructed from the elastances and airway resistances of each compartment. The H^1 minimal pressure profile taking this system from an initial inflation state $\mathbf{y_0}$ to a target inflation state $\mathbf{y_T}$ in time T can be generated using the formula

$$\mathbf{u} = \tilde{M}(\begin{bmatrix}\mathbf{y_T}\\ p_T\end{bmatrix} - \exp\left\{T\begin{bmatrix}A & B\\ 0 & 0\end{bmatrix}\right\}\begin{bmatrix}\mathbf{y_0}\\ p_0\end{bmatrix}) + p_0, \tag{2}$$

where p_0 and p_T are the initial and target pressures and $\tilde{M}$ is a specially constructed matrix of the form $\begin{bmatrix}M_y & M_p\end{bmatrix}$ [6, Chapter 4]. To generate an optimised pressure control we use eqn. 2 to formulate an optimisation for the control target

$$\mathbf{y}_T = \arg\min_{\mathbf{x}}\left[\mathbf{x}^* V^{-2}\mathbf{x} - \mathbf{r}^* V^{-1}\mathbf{x}\right], \tag{3}$$

$$\begin{bmatrix}M_y\\ -M_y\end{bmatrix}\mathbf{x} \le \begin{bmatrix}\mathbf{p}_{\max}\\ -\mathbf{p}_{\min}\end{bmatrix} + \boldsymbol{f}(\mathbf{y}_0, p_0, p_T, T). \tag{4}$$

Here V is a diagonal matrix of weightings for each compartment so that $(V^{-1}\mathbf{x})$ is a vector of clinically meaningful ratios such as the ventilation perfusion ratio or filling factor, $\mathbf{r}$ is a vector containing the desired ratios, $\mathbf{p}_{\max}$ and $\mathbf{p}_{\min}$ are boundaries on allowable pressure and $\boldsymbol{f}$ is a vector valued function. This system can be solved to produce optimal target states and subsequently optimal pressure controls as illustrated in figure 1. We investigate the behaviour of these optimal controls under errors in parameter estimation as performed with pseudo-absolute EIT.

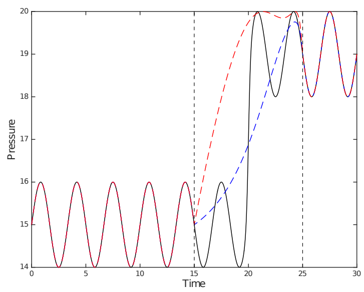

Figure 1: Comparison of H^1 minimal (blue) and optimised (red) PEEP steps to a demonstrative sinusoidal pressure profile (black).

4 Conclusions

Fast estimation of absolute conductivity values from EIT may allow construction of pressure controls optimised for recruitment while minimising damaging pressure gradients.

References

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