Automatic classification of lung tissue state from EIT images

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1. Introduction

One important application of EIT is for monitoring lung ventilation for use as a strategy to guide ventilation. Mechanical ventilation seeks to provide adequate gas exchange while avoiding overdistention (at high lung volumes and pressures) and lung collapse (at low lung volumes). Because lung disease is highly heterogeneous, it is important to develop a monitoring strategy which can classify lung tissue and quantify the fraction of lung tissue in ventilated, collapsed and overdistended state. Based on such a measure, an optimal mechanical ventilation strategy may be developed seeking to maximise ventilated tissue while minimising collapsed and overdistended tissue. In this paper, we describe an algorithm which attempts to perform automatic classification of the state of lung tissue from EIT time series images.

2. Methods

The algorithm uses time difference EIT images of short ventilation recordings at two different pressure levels — positive end-expiratory pressure (PEEP) for conventional ventilation or mean airway pressure (MAP) for high-frequency oscillatory ventilation (HFOV). The images are analysed in terms of ventilation-induced signal strength and mean conductance level of individual pixels (Figure 1-C,V). Images are fuzzified by assigning each pixel membership values (0–1) to three fuzzy sets — Lo, Average and Hi — depending on its value in relation to the image mean (Figure 1-FC,FV). At each pressure, a set of fuzzy if-then rules is applied to attempt identifying collapsed and overdistended regions of the lung (Table 1-States). Additionally, images at subsequent pressures are compared (Figure 1-$|\Delta C|$, ΔV, sign(ΔC), sign(ΔV)) to detect changes in state of individual pixels, e.g. opening or becoming overdistended (Table 1-Events). To obtain the final classification, the current state estimate and event information at each pressure are interpreted in context of the values from previous pressure steps, such that a pixel's state can only change if a suitable event has been detected (Figure 2).

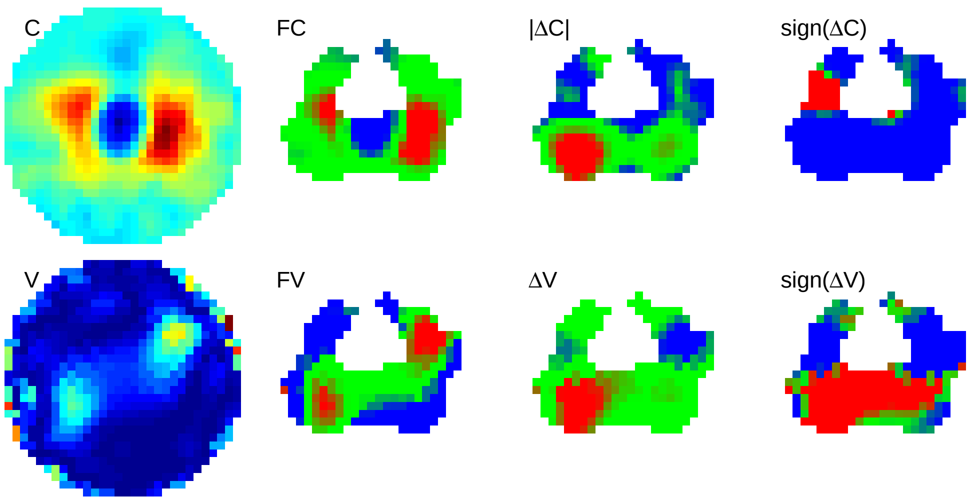

Figure 1. C: Conductivity image; V: Ventilation image; FC, FV: Fuzzified images; ΔC, ΔV: change from previous pressure step; sign: fuzzy equivalent of the sgn function. Legend: Hi Average Lo.

Table 1. Fuzzy inference rules defining states and events in individual pixels. Each inference rule is a fuzzy conjunction of the features listed.

	States		Events			
Feature	Collapsed	Overdistended	Opening	Collapsing	Overdistending	Recovering
Cond.	Hi	Lo	¬Lo	¬Lo	¬Hi	
Prev. Cond.	¬Lo	¬Hi				¬Hi
|ΔCond.|	Lo	¬Hi	Hi	Hi		
sign(ΔC.)			−	+	−	+
Vent.	Lo	¬Hi	¬Lo	Lo	¬Hi	¬Lo
Prev. Vent.	Lo	¬Hi	¬Hi		¬Lo	¬Hi
ΔVent.			Hi	¬Hi	Lo	¬Lo
sign(ΔV.)			+	−	−	+

Cond., C. – Conductivity; Vent., V. – Ventilation induced changes; Prev. – previous pressure step. See text for fuzzy definition of the sign function and the categories Lo, Hi.

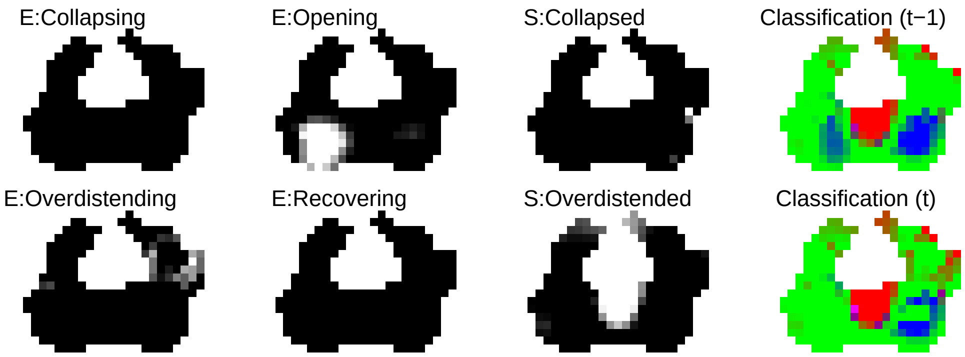

Figure 2. *Left:* Events (E) and states (S) recognised at MAP 25 color-coded in grayscale (■0–□1). *Right:* Classification at MAP 20 (top) and 25 (bottom). Legend: ■Overdistended ■Normal ■Collapsed.

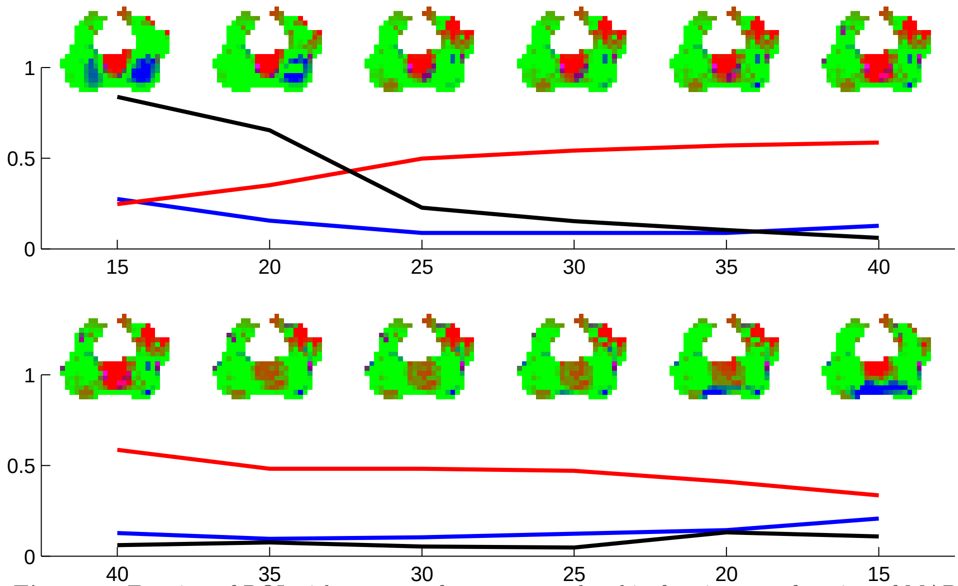

Figure 3. Fraction of ROI with non-zero fuzzy set membership fraction as a function of MAP for the inflation (top) and deflation (bottom) limbs of a recruitment manoeuvre in a pig with lung injury. Graph legend: - shunt fraction; - overdistended and - collapsed.

The algorithm has been applied to a set of data measured during HFOV in a porcine model of lung injury [3]. MAP is first increased from 15 to 40 mm H_2O, and then decreased back to 15 mm H_2O, in steps of 5 mm H_2O every 5 min. Measurements are conducted with the Goe-MF II EIT system with 16 electrodes applied equidistantly around the animals' chest (medioclavicular line). EIT time-difference images are reconstructed using the current version of the Graz consensus EIT reconstruction algorithm [1]. Ventilation-induced signal strength in each pixel is calculated using frequency spectrum analysis.

3. Results

Classification images from one animal are presented in Figure 1 along with tracings of the fraction of collapsed and overdistended lung tissue against shunt fraction. To calculate the fraction of lung tissue in a given state, a region of interest (ROI) was defined based on a recording of a pressure-volume manoeuvre prior to lung injury [2]. The classification images reflect the heterogeneous character of the injury. As MAP increases, areas identified as collapsed open up while others become overdistended, a trend that is largely reversed during deflation. Changes in fraction of collapsed lung correspond in time to changes in shunt fraction. As a result of the manoeuvre, there is less collapsed tissue in the final state than the initial one.

4. Discussion

In order to determine the success of this algorithm, it is necessary to validate the classifications. We are currently attempting to develop a method whereby the identified classifications may be tested. Preliminary results show that the algorithm appears to perform well on the inflation limb, but less so on the deflation limb. This is largely due to weakening of the ventilation-induced signal as lung opens up and difficulties in quantifying recovery from overdistention.

References

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