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Improving detection of patient ventilator asynchrony by deep learning through data augmentation based on modeling of pressure support ventilation

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Abstract— **The development of PVA detection algorithms is hampered by a lack of labelled data. In this study, the training of PVA detection methods was augmented with simulated data to improve the resulting performance. Although marginal, an increase in performance of about 1% was achieved by training the detection method with a ratio of 1:2 clinical to simulated data.**

I. Introduction

A patient ventilation asynchrony (PVA) is the mismatching between the timing of the mechanical ventilation MV and the spontaneous patient respiration. This mismatching can be detrimental to the quality of the MV, which in turn can lead to damage to the lungs, diaphragm, and respiratory muscles, longer ventilation duration and ICU stay, and a higher mortality rate [1]. However, detection of PVA currently requires observations of the air pressure, flow, and volume waveforms by clinical experts.

Detection methods for PVA are being developed but data scarcity forms a large problem. Consequently, in [2] simulations were suggested as a solution for the scarcity of labelled data. In this work, the breath segmentation will be trained and tested utilizing both clinical and simulated data. The results will provide insights on the effect of the simulated data on the performance of the breath segmentation algorithm.

II. Methodology

In this work, both clinical and simulated data was acquired and utilized.

1) Clinical data: The data consisted of 15 patients from the Fondazione I.R.C.C.S. Policlinico San Matteo (Pavia, Italy) with a total of 4275 recorded breaths [3].

2) Simulated data: The simulation model consisted of two parts, the model of the ventilator and the model of the patient, as described in [2]. Within this model, the parameters could be adapted to simulate different patient archetypes and ventilation settings.

On this data, the breath detection model previously described in [3] was trained. The training was performed in different ratios of clinical to simulated data. The clinical data were cross-validated and as a baseline, the performance of the detection model training only on clinical data was measured.

III. Results

Table I displays the resulting performances for the model when provided with different types of training data. The ratio of clinical data versus simulated utilized during training is indicated in parenthesis in the row "Trained on".

TABLE I: Performance of the breath detection algorithm when training with different ratio of clinical to simulated data (Clinical:Simulated)

Trained on	(1:0)	(1:1)	(1:2)	(1:3)
Precision	96.0%	96.0%	96.9%	96.6%
Recall	95.4 %	95.7%	96.5%	95.9%

IV. Discussion & Conclusion

In prior work, a promising method for breath segmentation was proposed [3], which was capable of detecting the start and end of the patient's inspiratory efforts. The limitations of this work were primarily related to the limited dataset size. In this work, we investigated the use of simulated data to improved the performance of the breath detection.

The utilization of the simulation in conjunction with clinical data was investigated to test its added value to improve the breath segmentation performance. A precision of 96.9% and recall of 96.5% was achieved by using a ratio of clinical to simulated data of 1:2 during training, as shown in Table I. This is an increase by roughly 1% for both the precision and recall compared to the network trained only on clinical data.

Future research should focus on expanding the dataset for the training, testing, and validation of PVA detection and classification methods. Simulations could provide a viable option for data augmentation. Developing reliable detection methods for PVA will allow for more detailed research into the effects of PVA on clinical outcomes.

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