Convolutional Neural Network for Respiratory Mechanics Estimation during Pressure Support Ventilation

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Abstract: In mechanically ventilated patients, some lung injuries can be reduced or avoided with therapy individualization, while the lung function is evaluated continuously, breath by breath. However, obtaining information on respiratory mechanics (respiratory system resistance and compliance) in the presence of respiratory effort is challenging, even if using invasive and complex procedures. The contribution of this work is to predict both respiratory system resistance and compliance over time using a convolutional neural network (CNN) and estimate the respiratory effort profile using the respiratory dynamics. Therefore, the approach used in this work was to generate a large amount of simulated data to feed a CNN so it could learn how to predict the correct values of the respiratory system resistance and compliance. Then, the respiratory effort was estimated by solving a first-order linear model. The main results showed a normalized mean squared error of 5.7% for the respiratory system resistance and 11.56% for compliance from Bland-Altman plots derived from the computational simulator. Finally, the method was validated using real data from an active lung simulator within which respiratory mechanics varied, and some ventilator settings were adjusted to mimic actual patient situations. The active lung simulator effort profile was obtained with a normalized mean squared error of 8.31% considering the use of an active lung simulator. The results have shown that the simulated data were valuable for the CNN training, while the performance over the real data suggested that the network was generalized accordingly for estimating respiratory parameters and effort profile.

Keywords: Mechanical Ventilation, Respiratory Mechanics, Respiratory Effort, Deep Learning, Convolutional Neural Networks.

1. INTRODUCTION

Lung injuries in mechanically ventilated patients can be avoided or minimized by continuously assessing the mechanics of the lungs at each respiratory cycle. Information on the patient's ventilatory dynamics, such as resistance and compliance, is important in adapting therapy, aiming to meet the patient's need and minimize the deleterious effects imposed by artificial mechanical ventilation. However, in the presence of breathing effort, the available options to continuously quantify breathing effort and respiratory mechanics are often invasive or complex (Heyer et al. 2002; Khirani et al. 2010).Although the measurement of breathing effort should be beneficial in some situations, it is not commonly evaluated in clinical practice (Vicario et al. 2015; Khirani et al. 2010).

The gold-standard method to evaluate respiratory effort requires an invasive esophageal balloon, using the esophageal pressure as a surrogate measure for pleural pressure (Bellani and Pesenti 2014;Vicario et al. 2015). Expiratory occlusions have also been used to measure the resistance and compliance of the respiratory system, two important quantities in the medical field to define the dynamics of the respiratory system, but this requires a rapid occlusion during ventilatory support (Lopez-Navas et al. 2014).

As a result, non-invasive approaches have been proposed to assess respiratory mechanics and breathing effort during invasive mechanical ventilation. The least-squares method, usually used to estimate the respiratory system parameters during passive ventilation, produces accurate results only if the patient is entirely passive or if the pressure from the esophageal balloon is also used (Khirani et al. 2010; Vicario et al. 2015). Vicario et al. 2015 proposed an interesting approach using quadratic programming and domain constraints, based on the physiology of respiratory effort, to assess ventilator pressure and flow data during assisted breathing. The presented constrained optimization algorithm provides reasonable estimates of respiratory effort and respiratory mechanics under certain conditions. However, this approach has limitations, such as its high computational cost and lack of robustness to approach this problem, since non-observability makes the problem possible but undetermined and, therefore, creates the need for external biological information to solve it. Thus, regressive methods that generalize the data patterns in order to obtain plausible results, considering the biological limitations of the human body, should be more successful.

The contribution of this work is to predict both respiratory system resistance and compliance over time using a convolutional neural network (CNN) and, finally, estimate the respiratory effort profile using the well-known first-order linear model of the respiratory system (Carvalho and Zin 2011) since, with these estimated parameters, the problem becomes the solution of a possible and determined system. Thus, in this work, we used a computational simulator to generate data for open airway pressure, airflow, and air volume to evaluate respiratory effort using three waveform profiles, and all variables of peak pressure, resistance, compliance, peak time, and finish time could be defined to simulate possible patient situations (Fresnel et al. 2014). Unlike the method proposed by Vicario et al. (2016) and other model-based algorithms which create their restrictions heuristically, our technique learns physiologically plausible results through data.

The remainder of this paper is organized as follows. Section 2 introduces some theoretical background techniques, which are deep learning techniques used in this work. Section 3 discusses the material and the methods used in this work, which is divided into respiratory system modeling, respiratory mechanics simulator, 1D-CNN setup, training and validation dataset, and active lung simulator dataset. Section 4 shows the results obtained using a 1D-CNN considering the setup presented in section 3. Section 5 discusses the results, presenting clinical implications and some limitations. Finally, section 6 concludes the work and shares ideas for future research.

2. THEORETICAL BACKGROUND

In this work, we used deep learning techniques, in specific, convolutional neural networks (CNNs). This technique was inspired by the functioning of the cat's visual cortex (Hubel and Wiesel 1962) and proposed initially to work with matrices. Recently, 1D-CNNs have been proposed and immediately achieved state-of-the-art performance levels in several applications such as personalized biomedical data classification and early diagnosis, structural health monitoring, anomaly detection, and identification in power electronics and electrical motor fault detection (Kiranyaz et al. 2021).

1D-CNN architectures were chosen due to their high capacity to detect characteristics present in the data. They can work with dimensionality in sampling, real-time applications, and low-cost hardware implementation. The compact and straightforward configuration of 1D-CNNs performs only 1D convolutions, which are scalar multiplications and additions, as seen in (1) (Goodfellow et al. 2016; Kiranyaz et al. 2021).

In the following subsections, we describe essential theoretical parts from CNN architecture.

2.1 CNN architecture

1) Convolutional layer: A vector of parameters, represented by $\mathbf{W}$, is defined as a convolutional filter to be learned. It is important to note that the operation used in a convolutional neural network does not correspond precisely to the definition of convolution used in other fields, such as engineering or pure mathematics (Goodfellow et al. 2016). In the case of (1), we can consider it as an inner product, but in general, for more dimensions, it is called cross-correlation.

$$\mathbf{V} * \mathbf{W} = \sum_{i}^{f-1} V[i]W[i], \tag{1}$$

where $\mathbf{V}$ and $\mathbf{W}$ are vectors of floating numbers with size equals to a hyperparameter called filter, an integer number, the variable i iterates between 0 until f-1, where f describes the dimensions of the parameter filter that will be used.

2) Max Pooling layer: The pooling layer's main function is to reduce the number of values, thus greatly improving computational time as well as controlling overfitting (Scherer et al. 2010; Girshick 2015).

3) Batch Normalization layer: Batch Normalization allows being less careful about initialization and learning rates (Ioffe and Szegedy 2015). Therefore, it fundamentally impacts network training: it makes the landscape of the corresponding optimization problem significantly more smooth. This ensures, in particular, that the gradients are more predictive allowing faster network convergence using an extensive range of learning rates (Santurkar et al. 2018).

2.2 CNN Hyperparameters

Convolution operations can be performed in several ways depending on the stride, kernel size, volume, padding, and the number of filters. The stride, represented by s, is the step that is carried out from one convolution operation to another. The kernel size describes the dimensions of the parameter filter f that will be used. The output volume is related to the dimension of the input, L_{in} for input length. The padding, represented by p, represents an addition of null values to the information to increase the size of the output or keep it constant (Goodfellow et al. 2016).

The selection of each of these hyperparameters not only defines how the convolutional operational will be performed but also the size of the output of each network layer. Equation (2) models the size of the output based on a 1D-CNN:

$$Output = \left\lfloor \frac{L_{in} + 2p\ - f}{s} + 1 \right\rfloor . \tag{2}$$

3. MATERIALS AND METHODS

3.1 Respiratory system modeling

The mechanical ventilator and patient set was modeled as a first-order system, in which the difference between the airway pressure ($P_{aw}(t)$) and the respiratory effort pressure ($P_{mus}(t)$) was described as the sum of the resistive ($P_{res}(t)$) and elastic ($P_{el}(t)$) pressures of the respiratory system (Carvalho and Zin (2011)). Equation (3) describe the modeled system, where R is the resistance, C is the compliance, $V(t)$ is the air volume, and $\dot{V}(t)$ is the airflow:

$$\begin{cases} P_{res}(t) = & R\dot{V}(t); \\ P_{el}(t) = & \dfrac{V(t)}{C}; \\ P_{aw}(t) - P_{mus}(t) = P_{res}(t) + P_{el}(t). \end{cases} \tag{3}$$

The quantities $P_{aw}(t)$, $V(t)$, and $\dot{V}(t)$ are readily available in mechanical ventilator, while respiratory mechanical parameters of resistance and compliance need to be estimated.

3.2 Respiratory mechanics simulator

A simulator proved to be extremely important in this research since the airflow, volume, and pressure waveforms are difficult to be obtained. Given this, some considerations were made regarding variables and types of curves capable of generating more realistic measurements. For example, we added noise in the simulated waveforms, delay in the ventilator trigger, different types of curves referring to the patient effort, and variations in respiratory rates to diversify the period of each respiratory cycle. The code is avaiable in gitlab [1] .

All parameters were randomly sampled, considering a uniform distribution, respecting physiologically acceptable values. The generated airflow, volume, and pressure waveforms were discretized, sampling frequency was 50 Hz and we used a fixed time window of 901 samples, which represents approximately 18 seconds of breathing. table 1 describes the minimum and maximum values for each parameter as well as their dimensions in respiratory dynamics. In addition to table 1, we input three different profiles of muscular pressure (P_{mus}) waveforms: sinusoidal, linear, and parabolic-exponential; and two pressure rise types for the ventilator control: linear and exponential.

Table 1. Simulator's parameters

Paramater	Minimun	Maximum	Dimension
Compliance	30	80	mL/cmH_2O
Resistance	4	30	cmH_2O.s/mL
Respiratory Rate	10	35	rpm
Peak Amplitude	-15	-5	cmH_2O
Peak Time	0.3	0.8	s
End Time	1	1.5	s

Compliance and Resistance are important values for the simulator since they are the dynamical constants which the first-order linear model requires. Respiratory Rate is the frequency measure between two respiratory cycles. Peak amplitude, Peak Time, and End Time are properties from *Pmus* defining the maximum amplitude (Peak amplitude), the difference of time between the start and the end of the inspiratory phase (reaching the peak amplitude), and finally, the end time which represent the period between the start and the end of the expiratory phase.

Importantly, ineffective effort and double triggering asynchronies were also implemented, which are frequent problems in patients under support ventilation and should be modeled to make the simulator closer to reality. The ineffective effort can be described as the failure of the ventilator to detect that the patient needs support pressure and, therefore, the mechanical ventilator does not provide airflow. On the other hand, the double triggering happens when the patient does not need the support pressure at a given time, but the ventilator triggers, which may be related to ventilator-induced lung injuries (Brochard 2016; Holanda et al. 2018).

Table 2. 1D CNN architecture, in the left column we describe the layer's type, and on the right side the input's dimension of each layer.

Layer	Dimension
Input	901x3x1
Conv1D	901x5x1
Batch Normalization	901x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	405x5x1
Conv1D	405x5x1
Batch Normalization	405x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	225x5x1
Conv1D	225x5x1
Batch Normalization	225x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	112x5x1
Conv1D	112x5x1
Batch Normalization	112x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	56x5x1
Conv1D	56x5x1
Batch Normalization	56x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	28x5x1
Conv1D	28x5x1
Batch Normalization	28x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	14x5x1
Conv1D	14x5x1
Batch Normalization	14x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	7x5x1
Conv1D	7x5x1
Batch Normalization	7x5x1
Activation	Leaky Rectified Linear Unit
Max Pooling	3x5x1
Conv1D	3x5x1
Batch Normalization	3x5x1
Activation	Leaky Rectified Linear Unit
Flatten	15x1
Dense	200x1
Dense	50x5x1
Output	2x1

[1] https://gitlab.com/ita-health-open/mastering-pmus

3.3 1D-CNN setup

After sampling the data with the generator described in the previous topic, a 1D-*CNN* is used to find patterns from airflow, the air volume, and airway pressure and correctly predict values of resistance and compliance, represented by R and C, respectively. table 2 describes the 1D CNN architecture, and Table 3 describes the hyperparameters used. We developed 1D-CNN algorithms using Python programming language, Tensorflow, and Keras library (Chollet et al. 2015).

Table 3. CNN hyperparameters

Hyperparameters	Value
Kernel Size (Conv1D)	5
Pool size (Pooling)	2
Bias (Conv1D)	False
Alpha (Leaky Relu)	0.1
Learning Rate (Adam)	0.001
Decay (Adam)	0.0001
Number of Minibatches	1

The idea is that the CNN is an inverse function of the process performed in the simulator, receiving the variables volume, airflow, and airway pressure, which are usually available in a mechanical ventilator setting, as inputs and the output will be the resistance and compliance variables, which challenging to measure using non-invasive methods. Equation (5) describes the function learned by the neural network:

$$CNN(\mathbf{V}, \dot{\mathbf{V}}, \mathbf{P}_{aw}) = (R, C), \tag{4}$$

where $\mathbf{V}$, $\dot{\mathbf{V}}$, and $\mathbf{P}_{aw}$ are volume, flow and airflow pressure, respectively, all easily sampled from mechanical ventilator.

3.4 Training dataset

A dataset composed of 60,000 samples was used for the neural network training. Each sample is a whole respiratory cycle containing airflow, air volume, and pressure waveforms, besides the used resistance and compliance for system dynamics. The neural network was training following (5), using 70% of the data for training, 15% for validation, and 15% for testing. In addition, a condition of training stop, called Early Stopping, was used to avoid overfitting. The condition was to stop iterating if the mean quadratic error of the validation set reached 10 consecutive values greater than the minimum obtained during the training.

3.5 Active lung simulator dataset

A dataset generated using an active lung simulator (ASL) was used, each sample obtained from ASL has a whole respiratory cycle containing airflow, air volume, and pressure data (de Macedo et al. 2019). The 1D-CNN was used following (5) as an evaluation of how well the network generalizes to deployment. In addition, the active lung simulator was configured with different setups, which were registered in table 4. To deal with the differences related to the sampling we adapted the ASL sampling (512 Hz) to the computational simulator (50 Hz).

Table 4. Setup of active lung simulator which are kept constant during the experiments

Parameter	Value
Frequency	512 Hz
Compliance	40 mL/cmH2O
Resistance	12 cmH2O.s/mL
Cycling off	25%
Slope	80%
PSV	5, 10, or 15 cmH2O

4. RESULTS

To evaluate the quality of results we used normalized mean squared error, *nmse*:

$$nmse = \frac{\|y - \hat{y}\|^2}{\|y - \bar{y}\|^2}, \tag{5}$$

where y is the ground truth value, $\hat{y}$ is the predicted value, and $\bar{y}$ is the average y value. The main results using the 1D-CNN showed that using the computational simulator described in subsection 3.2 obtained a normalized mean squared error of 5.7% for the respiratory system resistance and 11.56% for compliance. At the same time, the muscular pressure was obtained with a normalized mean squared error of 3.23%.

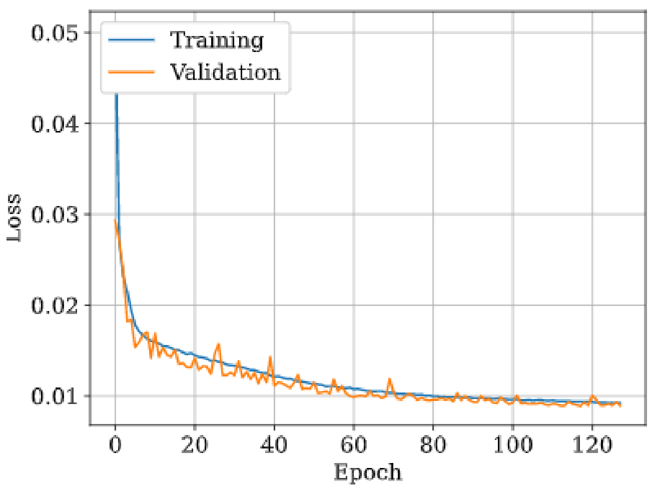

Fig. 1. Training and validation loss function over the number of epochs.

After training the 1D CNN, we tested the results using the Active Lung Simulator (ASL) dataset, using (3) with the dynamic constants predicted by the neural network, represented by Fig. 4 considering one patient which has compliance equals to 40 mL/cmH2O and resistance equals to 12 cmH2O.s/mL. Table 5 describes the performance achieved.

The results have shown that the simulated data were valuable for the 1D-CNN training, while the performance over the real data, i.e, data provided from the active lung simulator, suggested that the network generalized

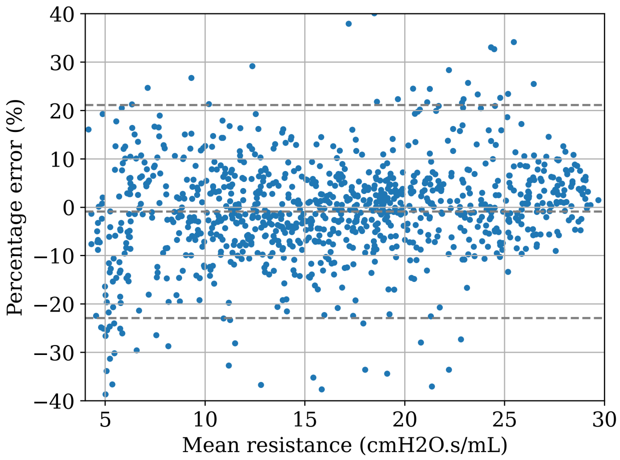

Fig. 2. In the y-axis we have the percentage error of the 1D-CNN for the ground truth resistance, whereas in the x-axis we have the average resistance value between the value predicted by the network and the ground truth, considering 1,000 samples from the test set generated by the computational simulator.

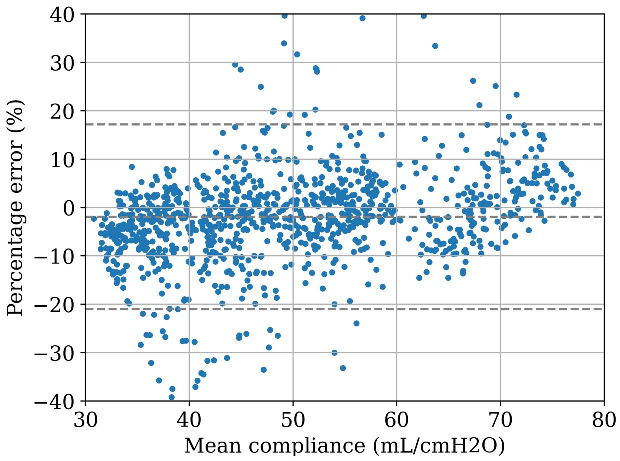

Fig. 3. In the y-axis we have the percentage error of the 1D-CNN for the ground truth compliance, whereas in the x-axis we have the average compliance value between the value predicted by the network and the ground truth, considering 1,000 samples from the test set generated by the computational simulator.

accordingly for estimating respiratory mechanics and effort profile, generating a normalized mean squared error of 8.31%, 0.8% for compliance, and 7.47% for resistance. The compliance error was lower than the training dataset due to the fact that it was a specific case where the configuration of resistance and compliance were well generalized by the CNN, which does not occurs with all possible configurations of R and C. Fig. 2 and Fig. 3 illustrate the results as Bland-Altman plots for the estimates of computational simulator dataset. The most relevant clinical implications for this results will be an advance as an essential tool for personalized medicine, for improving the capability of physicians to diagnose complex clinical conditions, and study the evolution of the breathing system throughout some treatment starts.

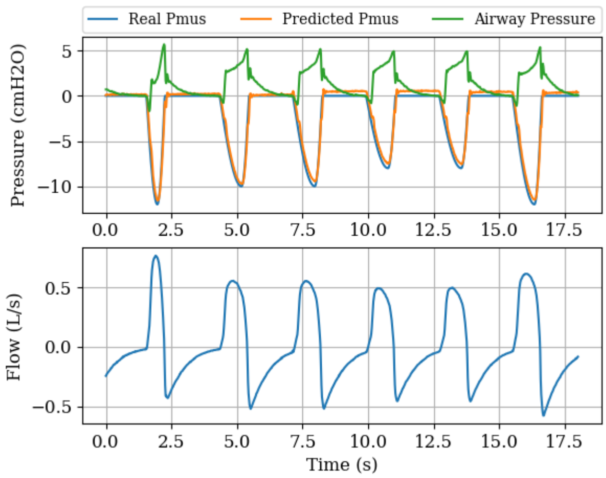

Fig. 4. Respiratory dynamical system measured by ASL and muscular pressure curve obtained after estimate both compliance and resistance.

Table 5. Performance's comparison between computational simulator test set and ASL dataset.

Paramater	Computational Simulator	ASL
Compliance	11.56%	0.8%
Resistance	5.7%	7.47%
Muscular Pressure	3.23%	8.31%

5. DISCUSSION

Non-invasive approaches have been proposed to assess respiratory mechanics and breathing effort during invasive mechanical ventilation. Unlike the method proposed by Vicario et al. (2016) and other model-based algorithms which create their restrictions heuristically, our technique learns physiologically plausible results through the data.

The CNN model relates airflow pressure, flow, and volume parameters to output values of resistance and compliance. Therefore, using only instantaneous data of pressure, flow, and air volume as input to our 1-dimension CNN. After predicting both parameters, we used the well-known first-order linear model of the respiratory system (Carvalho and Zin 2011) to obtain the respiratory effort profile.

Despite the use of the computational simulator to generate samples available for the model development due to the lack of real data, the CNN was successful in mapping the inputs to outputs with a normalized mean squared error of 8.31% considering ASL dataset. Therefore, this error achieved by the CNN model on independent test samples demonstrates that the Deep Learning approach can be effectively applied for predictive modeling in non-invasive approaches that have been proposed to assess respiratory mechanics and breathing effort during invasive mechanical ventilation. Notably, the CNN not only mapped the dynamic system but also was unaffected by a decrease in performance due to asynchrony problems encountered, whether it be double-triggering or innefective effort.

The low mean squared error of muscle pressure is attributed to the approach of first predicting the dynamic constants of the system, both resistance, and compliance with low mean squared errors, and then solving the linear system. The great advantage of a CNN is that it extracts the main characteristics of the volume, flow, and air pressure curves in order to predict such constants, this is important since CNN can deal with small variations, such as noise or even asynchronies present in the problem (Kiranyaz et al. 2021), and later uses the constants as invariant over the sampled interval. In addition, mapping constants with low errors promotes gains in clinical analysis, since doctors understand respiratory characteristics through these constants.

On the other hand, some limitations can be highlighted using this methodology.Regarding mathematical modeling, exposed in subsection 3.1, there is no single solution to the problem due to the fact that it is an undetermined system. Regarding the CNN approach, the need for data that represents the whole set of possibilities is important, but the difficulty for us obtaining real dataset makes the simulator the only possible approach, but just using a simulator affect directly the performance due to the fact that problems of distribution shift can be problematic (Fang et al. 2020). Another limitation is related to the choice of hyperparameters. In this research, the network structure was determined empirically. Given this, there is no guarantee that the hyperparameters used are optimal.

6. CONCLUSIONS AND FUTURE WORKS

The method presented for noninvasive estimation of respiratory effort, using pressure support ventilation, demonstrates the ability that the approach of convolutional neural networks has to accurately estimate the waveform profile assumed by each patient simulated by ASL, considering the particularities of each disease and according to the patient's clinical condition.Thus, this robust approach was necessary due to the need to generalize and interpret the data when using mechanical ventilators. Finally, the results demonstrate not only that the network presented reasonable generalization capacity but also that the approach through deep neural networks was achieved a good accuracy.

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