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Analyzing Patient-Ventilator Interaction with Neural Networks

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Abstract

This study investigates the integration of computational modeling and machine learning to analyze patient-ventilator interaction (PVI) in mechanical ventilation. One-compartment, multi-compartment and nonlinear models were developed to generate synthetic data that account for lung mechanics under various conditions. Utilizing synthetic data addresses the limitations of real clinical data availability. These datasets were used to train a residual neural network (ResNet) model for time-series classification which allows to predict PVI events effectively. The ResNet model that consists of convolutional layers and skip connections which captured complex relationships between physiological parameters to achieve a test accuracy of 89.27% and a test loss of 0.24. The framework offers a promising direction for personalized ventilation strategies that aims to enhance patient care in critical respiratory conditions. This integration makes a significant advancement in the management and optimization of mechanical ventilation approach using artificial intelligence (AI).

I. Introduction

Monitoring patient-ventilator interaction (PVI) is crucial for effective mechanical ventilation, particularly in patients suffering from acute respiratory failure or those depending on long-term ventilation support. Adequate ventilation is achieved through synchronization of the patient's spontaneous breathing efforts and the mechanical support of the ventilator. This synchronization minimizes patient effort and reduces the risk of ventilator-induced lung injury [1]-[2]. Despite advancements in understanding PVI, challenges persist in maintaining optimal patient-ventilator synchronization. Temporal mismatch between the patient's & mechanical ventilator's assistance is called patient-ventilator asynchrony, which is very common on critically ill patients [3]. Identifying asynchrony typically involves analyzing airway pressure and flow curves and simultaneously monitoring respiratory muscle activity. Modern computational methods, such as neural networks (NN) and other machine learning (ML) techniques, have further enhanced the analysis and optimization of PVI [4]. These approaches leverage patient-specific data to predict optimal ventilator configurations and have demonstrated notable improvements in accuracy, sensitivity and precision in simulated test results. The code developed in this paper offers flexibility and precision in simulating scenarios of normal and impaired lung function. Thus, outputs such as volume, flow and pressure signals, provide valuable insights into the impacts of various ventilation parameters [5]. Through the integration of mathematical modeling (MM) & data-driven approaches, this study aims to enhance the understanding of ventilator dynamics & offers a robust framework for analyzing ventilator settings. This integration of models & artificial intelligence (AI) provides a promising direction for improving outcomes in respiratory care [6], offering the potential to facilitate the management of mechanically ventilated patients.

II. Material and Methods

MATLAB and Python were used as software tools for this study. MATLAB was used for modeling the respiratory system and simulating various curves from different compartment models. Python was set up for deep learning with TensorFlow on an NVIDIA A100 GPU (MIG - 5GB) which was a virtual environment in JupyterLab provided by Technische Hochschule Lübeck. The respiratory system was represented using three different types of models: the one-compartment, multi-compartment and nonlinear-compartment model. Synthetic patient data were generated using differential equation solvers. The obtained synthetic data was used as an input for the ML algorithms. This allows the scaling and controlled training of the models without considering actual patient records.

II.I. Modeling the Respiratory System

The basic equations for the circuit diagram of the different compartment models were based on [5]-[7]. The equations reflecting one-compartment, multi-compartment and nonlinear-compartment models were then prepared and solved accordingly.
The **one-compartment model** has been designed according to system dynamics equation (1) and calculated as described by Bates et al. [7]:

$$P_{aw} = V * \frac{1}{C} + R * \dot{V} + P_{mus}, \tag{1}$$

where P_{aw} is the airway pressure, V is the lung volume, C is the lung compliance, R is the airway resistance, $\dot{V} = dV/dt$ is airflow and P_{mus} is the patient's muscle pressure. Inspiratory pressure (IP) is represented as time-varying rectangular pulses, while P_{mus} is a sinusoidal waveform with exponential decay over respiratory cycles to simulate muscle effort. P_{mus} and P_{aw} are calculated as time-varying inputs, and V and $\dot{V}$ are derived using ordinary differential equation solvers. For the **two-compartment model**, the circuit has been designed and calculated as described by Bates et al. [7]:

$$\dot{V}_2 = \frac{P_{aw} - \frac{V_2}{C_2}\left(\frac{R_1}{R_3}+1\right) + \frac{V_3}{C_3}\frac{R_1}{R_3}}{\frac{R_1 R_2}{R_3} + R_1 + R_2}, \tag{2}$$

$$\dot{V}_3 = \frac{P_{aw} - \frac{V_3}{C_3}\left(\frac{R_1}{R_2}+1\right) + \frac{V_2}{C_2}\frac{R_1}{R_2}}{\frac{R_1 R_3}{R_2} + R_1 + R_3}. \tag{3}$$

Here, again, V denotes volume, R resistance, and C compliance. The indices 2 and 3 correspond to the right and left lung respectively. The resistance of the trachea leading to the lungs is R_1. Again, these equations were then implemented in MATLAB to generate the synthetic data.
For the **nonlinear-compartment model**, the complete pressure-volume relationship of the lung, ranging from residual volume (V) to total lung capacity, is best characterized by a sigmoidal function, as described in the equation (4) [7]:

$$V = a + \frac{b}{1 + e^{-\frac{(P_{tp}-c)}{d}}}, \tag{4}$$

where P_{tp} is transpulmonary pressure, i.e, the pressure difference between the alveolar pressure and the pleural pressure and a, b, c & d are adjustable parameters that define the specific characteristics of the curve. To determine the compliance C, the derivative of V with respect to P_{tp} was computed using the equation (5). The derivative was expressed in its simplified form after applying the quotient rule.

$$C = \frac{dV}{dP_{tp}} = \frac{b e^{-\frac{(P_{tp}-c)}{d}}}{d\left(1 + e^{-\frac{(P_{tp}-c)}{d}}\right)^2}. \tag{5}$$

Equation (5) has been implemented in MATLAB to simulate the breathing system for nonlinear model.

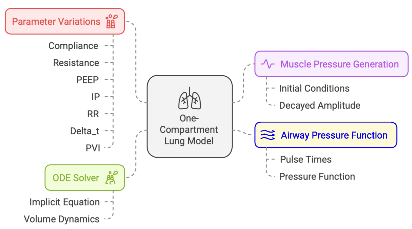

Figure 1: Schematic diagram of a PVI model

Figure 1 outlines the key parameters used in modeling the respiratory system, categorized into six components: Inspiratory Pressure (IP), trigger types (synchronous, delayed, auto-trigger, ineffective), lung compliance, airway resistance, PEEP range, and pressure levels. These parameters formed the basis for simulating respiratory behavior and analyzing physiological variations. The models produced synthetic $\dot{V}$, P_{mus}, and V curves that simulated the interaction between ventilator settings and respiratory mechanics. Curves for P_{aw}, P_{mus}, $\dot{V}$ and V were generated at a sampling rate of 0.1 Hz for 30 second patches yielding 300 sample points per simulation. The data is then saved in CSV format for machine learning. One- & two-compartment models were solved using MATLAB's ODE45 and ODE15i solvers, with the ODE15i solver specifically used for nonlinear-compartment models due to its capability to handle implicit equations. The obtained equation was then implemented in MATLAB to generate the synthetic data.

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II.II. Integration of synthetic data with machine learning algorithm

Real clinical data was scarce and subject to strict privacy regulations requiring extensive ethical approvals and consent processes. This could be time consuming making it difficult to gather enough samples for robust model training. Synthetic data can be produced in abundance to meet up the requirements of comprehensive datasets that include a variety of edge cases and rare events. In our study, a residual neural network (ResNet) architecture was utilized to classify and analyze synthetic respiratory data. The ResNet architecture, known for addressing the vanishing gradient problem through residual connections, was adapted for time-series classification to predict PVI events. The dataset, loaded from a CSV file, included features such as P_{aw}, P_{mus}, $\dot{V}$ and V with PVI types as the four class labels (synchronous, delayed, auto-trigger, ineffective). The model architecture featured a convolutional neural network (CNN) with ResNet blocks, employing convolutional layers, max-pooling, and dropout layers to extract features and mitigate overfitting. Training spanned 20 epochs with a batch size of 32, and validation was conducted on a separate test set. Performance was evaluated based on test set loss and accuracy, with predictions compared to true labels to determine accuracy.

III. Results and Discussion

The results demonstrate the simulation behavior of the respiratory system of three different modeling approaches: the one-compartment model, the two-compartment model, and the nonlinear-compartment model.

III.I. Simulation of the patient breathing

Figure 2 represents the simulation of **one-compartment model**. The simulation captures fundamental respiratory mechanics, highlighting a strong correlation between P_{mus}, P_{aw}, V & $\dot{V}$. While effective for basic simulations, the one-compartment model lacks the capacity to capture regional lung dynamics or nonlinear interactions. Figure 3 shows the **two-compartment model**. The simulation provides an enhanced representation of the respiratory system by introducing differential behavior between the left and right lung. The distinct lung volume curves (V_2 & V_3) and flow rates ($\dot{V}2$ & $\dot{V}3$) illustrate intercompartmental interactions, revealing heterogeneity in lung mechanics. This model adds complexity by accounting for variability in compliance and resistance between compartments, offering a more realistic depiction of respiratory dynamics compared to the single-compartment model. Figure 4 represents the **nonlinear-compartment model**. It introduces physiological realism by incorporating nonlinear resistance and compliance effects. The resulting P_{aw}, V and $\dot{V}$ curves exhibit deviations from the linear patterns observed in the simpler models. These nonlinear dynamics more closely mimic the behavior of the respiratory system under realistic conditions, capturing subtleties such as dynamic airway resistance and non-uniform lung mechanics.

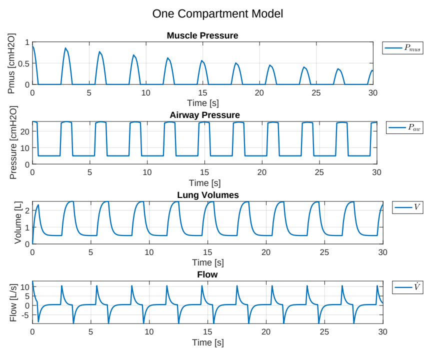

Figure 2: Simulation results of the one-compartment model

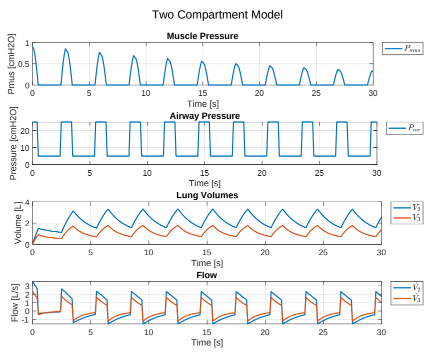

Figure 3: Simulation results of the two-compartment model

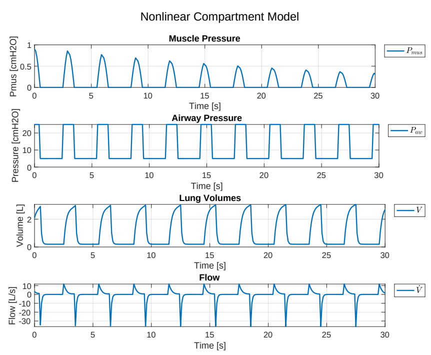

Figure 4: Simulation results of the nonlinear compartment model

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III.II. Data integration with neuronal network

Our customized ResNet model was able to recognize different breathing patterns by classifying the data into specific breathing triggers. It used a method called a softmax function to make these classifications, which is commonly used in machine learning for such tasks. As a first step in this work, only the linear model was used to generate the training and test data, but the framework can be easily extended to the other models. Synthetic data were integrated to evaluate how accurately our model could identify breathing patterns and detect any abnormalities. For training, 2130 datasets were used (426 each for synchronous, delayed trigger, auto-trigger, and ineffective trigger). The accuracy was evaluated on 559 test datasets (100 synchronous, 100 delayed trigger, 120 auto-trigger, 120 ineffective trigger). The results were promising: our model achieved a test loss of 0.24 and a hit rate of 89.27%. This shows that our approach was quite effective in predicting different events related to ventilator settings. Overall, this project demonstrated how deep learning, especially using ResNet, may significantly improve the management of ventilator settings by accurately predicting various events based on P_{mus}, $\dot{V}$, and V data.

IV. Conclusion

In conclusion, this research successfully demonstrated the integration of computational modeling and deep learning techniques to enhance the understanding and optimization of PVI. By developing and simulating one-compartment, two-compartment and nonlinear models, synthetic data were generated that effectively represented lung mechanics under various conditions. The use of a ResNet model for time-series classification proved to be a valuable approach in predicting PVI events enabling the identification of various respiratory patterns and anomalies. The ResNet model, equipped with convolutional layers and skip connections, effectively captured different patterns of patient-ventilator interaction. The framework presented here offers a promising direction for developing personalized ventilator strategies, ultimately enhancing patient care in critical respiratory conditions and paving the way for further advancements in respiratory care using AI.
Despite the promising results, this research has several limitations. The deep learning models require extensive labeled data for training, which was difficult to obtain. The prepared models takes into consideration the general synthetic data lacking diverse patient populations and conditions. Future work should focus on validating the trained ResNet on real patient data and developing data-efficient models using transfer learning and semi-supervised learning to address data limitations. Advancing explainable AI methods will enhance the interpretability of model predictions. Research should also explore personalized medicine approaches, tailoring models to individual patients for more precise treatment recommendations.

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Author's statement

Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the german Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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