Monitoring Lung Mechanics during Mechanical Ventilation using Machine Learning Algorithms

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Abstract—Evaluation of lung mechanics is the primary component for designing lung protective optimal ventilation strategies. This paper presents a machine learning approach for bedside assessment of respiratory resistance \(R\) and compliance \(C\). We develop machine learning algorithms to track flow rate and airway pressure and estimate \(R\) and \(C\) continuously and in real-time. An experimental study is conducted, by connecting a pressure control ventilator to a test lung that simulates various \(R\) and \(C\) values, to gather sensor data for validation of the devised algorithms. We develop supervised learning algorithms based on decision tree, decision table, and Support Vector Machine (SVM) techniques to predict \(R\) and \(C\) values. Our experimental results demonstrate that the proposed algorithms achieve 90.3\%, 93.1\%, and 63.9\% accuracy in assessing respiratory \(R\) and \(C\) using decision table, decision tree, and SVM, respectively. These results along with our ability to estimate \(R\) and \(C\) with 99.4\% accuracy using a linear regression model demonstrate the potential of the proposed approach for constructing a new generation of ventilation technologies that leverage novel computational models to control their underlying parameters for personalized healthcare and context-aware interventions.

I. INTRODUCTION

Mechanical ventilation is one of the most widely used life-saving interventions in hospitals that affects millions of lives of patients with acute respiratory failure or compromised lung function caused by chronic lower respiratory diseases, cystic fibrosis, neuromuscular disease, spinal cord injuries, pneumonia, sepsis, or heart disease. In the United States, nearly 40\% of patients admitted to an intensive care unit (ICU) require mechanical ventilation. This amount of mechanical ventilation accounts for 12\% of the total hospital costs [1], [2]. Despite its life-saving potential, the pressure control mechanical ventilators are known to cause physiological stress and strains leading to ventilator-induced lung-injuries (VILI) [3], [4].

ARDS network recommended that the risk of VILI in pressure control ventilation can be reduced by keeping the tidal volume below 6 ml/kg of predicted bodyweight and plateau pressures below 30 cmH\(_2\)O [5]. Nevertheless, depending on the patient’s lung mechanics, VILI may occur even with the low tidal volume pressure control ventilation [6]. Another alternative for conventional pressure control ventilation is high-frequency ventilation (HFV), which delivers small tidal volumes at a rate of more than 150 breaths/minute. Several HFV techniques such as high-frequency oscillatory ventilation and high-frequency percussive ventilation have been proposed to provide improved oxygenation and lung protection for severe lung diseases [7], [8]. However, due to the complex nature of HFV waveforms and in absence of large controlled randomized studies to sufficiently assess the role of HFV in reducing mortality and morbidity, respiratory intensivists heavily rely upon pressure control ventilation [9].

Prior research reported that personalized ventilation approaches could prevent VILI [10]. Each patient and their state of the disease are unique, and therefore, mechanical ventilation should be optimized according to the patient’s lung mechanics. The most important parameters that characterize a patient’s lung mechanics are \(R\) and the \(C\). \(R\) measures the resistance to airflow in the respiratory airways, which increases during obstructive and restrictive diseases and the presence of mucus plugs. \(C\) measures the volume distensibility of the lung tissue. Certain mechanical ventilators allow to perform rapid flow interruption maneuvers [11], [12], such as the end-inspiratory pause and end-expiratory pause to assess \(R\) and \(C\). However, these values do not represent the actual respiratory mechanics of the patient. There have been limited attempts at real-time monitoring.
of respiratory mechanics [13] based on the linear first-order model of respiratory mechanics [14]. These models, however, have remained largely inaccurate for personalized ventilation in continuous and real-time patient monitoring settings.

To address the identified research gaps, we develop a novel computational approach to monitor lung mechanics continuously and in real-time. Our approach is based on machine learning algorithms that operate on ventilator waveforms of pressure and flow rate. We design and validate such machine learning algorithms for pressure control ventilation using experimental lung models with known $R$ and $C$. To the best of our knowledge, the utility of machine learning algorithms for monitoring lung mechanics has not been explored in the past.

II. SYSTEM AND METHODS

In this section, the data collection setup and procedures are discussed along with the data analysis and algorithm design.

A. General Approach

We develop a predictive model based on supervised learning methodologies. The algorithms are developed based on ventilator sensors that describe flow rate and airway pressure. We govern an experiment to gather and label such sensor data with fixed resistance and compliance values. These fixed resistance and compliance values are then used as ground truth measurements for algorithm training and performance analysis. In developing the computational models, we examine two groups of machine learning algorithms, namely classification and regression. A classification algorithm allows us to classify the ventilator waveforms of pressure and flow rate as a discrete label that represents combined values $R$ and $C$. Although a classification algorithm can provide a high level categorization of resistance and compliance, it cannot describe resistance and compliance as real values. Thus, we also explore the utility of regression models to describe resistance and compliance as linear functions of the ventilator waveforms. The regression is utilized for estimating the relationship between changes in the pressure ($P$) and the flow rate ($Q$), and the value of $R$ and $C$.

B. Data Collection

The setup for our experimental measurement of the ventilator waveforms is shown in Fig 1. The mechanical ventilator, LTV 950 (Pulmonetic Systems), was connected to a test lung (Quicklung, Ingmar Medical, and Pittsburgh, PA, USA). The airway pressure and flow rate in the ventilator circuit were measured using a 16-channel digital pressure sensor array, DSA 3217 (Scanivalve), and a heated Fleisch type pneumotachograph (i.e., Hans Rudolph 3700), respectively. The airway pressure and flow rate in the ventilator circuit were measured using a 16-channel digital pressure sensor array, DSA 3217 (Scanivalve), and a heated Fleisch type pneumotachograph (i.e., Hans Rudolph 3700), respectively. The ventilator was set at peak inspiratory pressure and PEEP of 30 cmH$_2$O and 10 cmH$_2$O, respectively. The respiratory rate and the inspiratory time to the expiratory time (I:E ratio) for the ventilator were set at 20 breaths/min and 1:1, respectively. Four sets of experiments were performed by varying the C (10 and 20 ml/ cmH$_2$O) and R (5 and 20 cmH$_2$O /l/s) of the test lung. This experimental setup is similar to the one report by prior research. For example, authors in [15] performed nitrogen washout measurements in pressure control and high frequency percussive ventilations using a similar setup.

C. Algorithm Development

Our hypothesis is that the collective values of pressure and flow rate of lungs are unique and can be accurately detected based on machine learning classification algorithms. Our data processing pipeline includes integration of feature selection and data fusion algorithms that allow us to detect $R$ and $C$ by tracking the amount of pressure and flow rate.

Machine learning approaches have shown promise when a straightforward mathematical model cannot be extracted or building the model is too expensive. The collected sensor data in our experiments are used to develop machine learning algorithms that estimate resistance and compliance. The process of developing a machine learning algorithm for the application discussed here includes the following three main steps: (1) signal segmentation; (2) feature extraction; and (3) classifier training. We designed a MATLAB tool to divide the signals into segments of varying sizes ranging from 10 milliseconds to 7 seconds using a sliding window over the input signal. The raw signals can be redundant and non-informative enough to sufficiently distinguish among various classes. Therefore, we extract a set of representative features from the raw data. The resulting features and their associated labels are then used for classifier training. Supervised machine learning techniques require training data to build the predictive model. Training data consists of two parts: $X$ is a set of input features; $Y$ is a finite set of output labels; and $F(X)$ is a function for mapping $X$ to $Y$. The classification algorithm generates an output label $y_i \in Y$ for a given input $x_i \in X$. 

![Fig. 1: Experimental setup for airway pressure and flow-rate measurement using the LTV 950 unit.](image-url)
TABLE I: Class labels for each combined \( R \) and \( C \) level.

<table>
<thead>
<tr>
<th>Resistance (R)</th>
<th>Compliance (C)</th>
<th>Class Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>20</td>
<td>10</td>
<td>3</td>
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<tr>
<td>20</td>
<td>20</td>
<td>4</td>
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</tbody>
</table>

To develop a classifier that estimates \( R \) and \( C \), we grouped \( R \) and \( C \) values into several categories. For example, our data collection resulted in four different categories each of which indicates one \( R-C \) level. The labels are based on the combined \( R-C \) values. The four scenarios include (1) \( R=5, C=10 \); (2) \( R=5, C=20 \); (3) \( R=20, C=10 \); and (4) \( R=20, C=20 \). We intend to examine if the system is capable of recognizing the \( R-C \) level by observing \( P \), Volume (\( V \)), and \( Q \). The class labels and corresponding \( R-C \) values are shown in Table I.

\( \text{Table 2}: \) The training data with labeled instances were used to develop three types of classifiers including decision tree, decision table, and support vector machine algorithms. We assessed the accuracy of our classifiers using the collected experimental data. We used 10-fold cross validation as our validation method (i.e., 90% of the data were utilized for training and the remaining 10% for testing, and the process was repeated 10 times to ensure that each input instance is used as a test example once). The confusion matrices for different classifiers are shown in Table II. Performance parameters presented in this paper have the following definitions: Precision (\( P \)) refers to proportion of instances which truly belong to a class to the total number of instances classified as that class; Recall (\( R \)) represents the proportion of truly classified instances divided by the total number of instances; F-Measure is a combined measurement of precision and recall which indicates robustness of the classifier and is given by

\[
F_{\text{Measure}} = 2 \times \frac{P \times R}{P + R}
\]

Finally, ROC refers to the area under Receiver Operating Characteristic (ROC) curve; the closer it is to 100%, the better the classifier is.

The results for accuracy, precision, recall, F-Measure, and ROC using these three classifiers are shown in Fig 3a. As shown in these tables, our approach achieves 90.3%, 93.1%, and 63.9% accuracy in assessing \( R-C \) levels using decision table, decision tree, and SVM, respectively.

We also trained a regression model for estimating the \( R-C \) levels. We performed regression on data with various moving window sizes ranging from 10 milliseconds to 7 seconds. The \( R^2 \) value of the regression model varied from 0.03 to 99.4, respectively. The results are shown in Fig 3b.

IV. CONCLUSIONS AND FUTURE WORK

In this study, we proposed a novel approach to estimate \( R \) and \( C \) levels based on flow rate and airway pressure in mechanic ventilation systems. Our supervised learning approach finds critical applications in bedside monitoring of lung mechanics in pressure control ventilation. We presented an approach to train machine learning classifiers for real-time detection of \( R \) and \( C \) using time series signals of flow rate and airway pressure. Experimental data were collected by connecting a pressure control ventilator to a test lung model. Our data demonstrated that decision table and decision tree classifiers obtain only 9.7% and 6.9% error in assessing \( R-C \) scores. Using a regression model, our system reaches 99.4% accuracy in detecting \( R-C \) levels.
Further, the machine learning algorithms can be extended to predict the respiratory mechanics from complex waveforms of HFV techniques.

V. ACKNOWLEDGEMENT

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REFERENCES


The machine learning methods developed in this study using a test lung are a good starting point for future animal and clinical testing of real-time, continuous, and close-loop mechanic ventilation. These methodologies can be tested with ICU patient’s data for pressure control ventilation. Further, the machine learning algorithms can be extended to predict the respiratory mechanics from complex waveforms of HFV techniques.