Monitoring Lung Mechanics during Mechanical Ventilation using Machine Learning Approach

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Abstract—Evaluation of lung mechanics is the primary ingredient 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 developed machine learning algorithms that track real-time waveforms of flow rate and airway pressure to detect R and C. An experimental study was performed by connecting a pressure control ventilator to a test lung that simulates various R and C values to gather data for validation of the algorithms. We developed predictive techniques based on supervised learning tools using different methodologies, i.e., regression analysis, tree-based, and table-based. Our system achieves accuracies of 90.27%, 93.05%, and 63.89% in the assessment of respiratory R and C using decision table, decision tree, and Support Vector Machine (SVM), respectively. Using Linear Regression model, we estimated values of R and C with 99.44% accuracy.

1. 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 USA, nearly 40% of the intensive care unit (ICU) patients require mechanical ventilation, which accounts for 12% of the total hospital costs [1], [2]. Despite its life-saving potential, the pressure control mechanical ventilators are known for causing unphysiological stress and strains and resulting ventilator-induced-lung-injuries (VILI) [3], [4].

ARDS network [5] recommended that the risk of VILI in pressure control ventilation can be reduced by keeping the tidal volume below 6 ml per kg of predicted bodyweight and plateau pressures below 30 cmH₂O. 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 per minute. Various types HFV techniques, such as high-frequency oscillatory ventilation and high-frequency percussive ventilation have been found to provide improved oxygenation and lung protection for severe lung diseases [7], [8]. However, due to lack of understanding of the complex waveforms in HFV and 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].

Marini [10] reported that individualized ventilation approach could prevent VILI. Each patient and their state of the disease are distinctive, and therefore, mechanical ventilation should be optimized according to the patient’s lung mechanics. The most important parameters that characterize the patient’s lung mechanics are the respiratory resistance (R) and the compliance (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 some attempts at online monitoring of respiratory mechanics [13] based on the linear first-order model of respiratory mechanics [14], but these models are not accurate.

We aim to develop online monitoring of lung mechanics by employing a machine-learning algorithm that tracks ventilator waveforms for pressure and flow rate. The current manuscript focuses on the validation of the machine-learning algorithm for pressure control ventilation in test lung models with known values of R and C. This method could be later tested with ICU patient’s data for pressure control ventilation. Further, the machine learning algorithm will be extended to predict the respiratory mechanics from complex waveforms of HFV techniques.

Our hypothesis is that the collective values of pressure and flow rate of lungs is 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 values of pressure and flow rate.

2. System Design and Analysis

In this section, the architecture of the system is discussed and the data analysis process is explained in detail.

2.1. Architecture

We developed a predictive technique based on supervised learning methodologies. There are different classifiers such as probability-based, rule-based, etc. In this paper we utilized three different types of methodologies: regression analysis; tree-based; and table-based. Regression analysis is for processing the data statistically and finding a relationship between the problem’s variables. In this paper the regression is utilized for estimating the relationship between the changes in P and Q, and the value of R and C. In this paper, we utilized linear regression and support vector machine (SVM). The tree-based approach is decision tree classifier, which is chosen due to scalability and simplicity. Decision tree is similar to IF-ELSE evaluation. Decision table is the tree-based approach that is like SQL tables. More than one condition can be checked at a time. Machine learning approaches are utilized when a straightforward mathematical model cannot be extracted or building the model is too expensive. Machine learning technique requires training data to build the 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 is the function that gets \( x_i \) and generates an output label \( y_i \).

2.2. Data Collection

The setup for the experimental measurement of the ventilator waveforms is presented in Fig 1. The mechanical ventilator, LTV 950 (Pulmonetic Systems) was connected to a test lung (Quicklung, Ingmar Medical, and Pittsburgh, PA, USA). Airway pressure and the flow rate in the ventilator circuit was measured using a 16-channel digital pressure sensor array, DSA 3217 (Scanivalve) and a heated Fleisch type pneumotachograph (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. Dutta et al. [15] performed nitrogen washout measurements in pressure control and high frequency percussive ventilations using a similar setup.

2.3. Data Processing

After collecting the data it is transferred to the server. Later, the data is processed in three steps: (1) signal segmentation; (2) feature extraction; and (3) classifier training. We developed a MATLAB tool to segment the data into different window sizes (10 ms-7s). The raw training data can be redundant and non-informative. Therefore, we extract a set of derived values called features from the raw data. This resulting features and their associated label are then fed to the system for training classifiers.

3. Experimental Result

To recognize R and C level, four different scenarios are considered. The labels are based on the R-C levels. The experimental scenarios include (1) R=5, C=10; (2) R=10, 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 Pressure (P), Volume (V), and Flow-rate (Q). Data was collected in the frequency of 2 milliseconds in fixed R-C level. Fig 2 shows a raw signal of the data (a) 2-D demonstration of P-T and (b) 2-D demonstration of Q-T. After collecting the data and transmitting it to the server, we first extract an exhaustive set of features during ‘Feature Extraction’ process. These features are extracted from raw data removing the column for time in moving window of 10 ms to 2 s. The instances of all four levels are then combined to form a larger dataset. The extracted features from both pressure and flow rate include a set of eight statistical features (i.e., ‘minimum’, ‘maximum’, ‘mean’, ‘root mean square (rms)’, ‘signal amplitude’, and ‘peak to peak amplitude’).

The training data with labeled activities were used to develop decision tree (tree-based), decision table (rule-based), and support vector machine (SVM) (function-based) classification algorithms. We assess the accuracy of our classifiers using the collected experimental data. For designing the
(a)

(b)

Figure 2: Raw signal demonstrations of the, a) P-T, and b) Q-T.

TABLE 1: The number of instances, each row corresponds to a day, and each column is associated with one phase of the experiment

<table>
<thead>
<tr>
<th>R</th>
<th>C</th>
<th>Label</th>
</tr>
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<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>10</td>
<td>10</td>
<td>3</td>
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<tr>
<td>10</td>
<td>20</td>
<td>4</td>
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</table>

We developed a classifier where each label represents an R-C level. The labels are shown in Table 1.

We used 10-fold cross validation as our validation method. The confusion matrices for different classifier are shown in Table 2. Performance parameters presented in these graphs 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 3 respectively. The result is shown in Fig 4.

4. Conclusion and Future Direction

In this study, supervised learning based algorithms were proposed for bedside monitoring of lung mechanics in pressure control ventilation. We presented an approach to train machine learning classifiers for detection of real-time respiratory resistance and compliance using time signals of flow rate and airway pressure. Experimental data were collected by connecting a pressure control ventilator to a

TABLE 2: Confusion Matrix for different settings

(a) Error of classifying using Decision Table is 9.73%

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>← Classified As</th>
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<td>0%</td>
<td>0%</td>
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<td>3%</td>
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<td>0%</td>
<td>0%</td>
<td>b=2</td>
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<td>0%</td>
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<td>88%</td>
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</table>

(b) Error of classifying using Decision Tree is 6.95%

<table>
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<th>b</th>
<th>c</th>
<th>d</th>
<th>← Classified As</th>
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</tr>
<tr>
<td>0%</td>
<td>97%</td>
<td>3%</td>
<td>0%</td>
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</tr>
<tr>
<td>13%</td>
<td>0%</td>
<td>87%</td>
<td>0%</td>
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<td>6%</td>
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<td>94%</td>
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(c) Error of classifying using Support Vector Machine is 36.11%

<table>
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<th>b</th>
<th>c</th>
<th>d</th>
<th>← Classified As</th>
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<td>37%</td>
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</table>
Figure 3: The performance of classifiers

Figure 4: Performance of Linear Regression by increasing the window size from 10 milliseconds to 7 seconds

test lung model. Our data demonstrated that using decision table and decision tree we only have 9.73% and 6.95% error in assessing R and C. Using regression, our system reaches 99.44% accuracy in detecting R and C. The machine learning methods developed in this study using a test lung is a good starting point for future animal and clinical testing of these methods.

References


