Introducing an Intelligent Mechanical Ventilation Framework

Computer Integrated Surgery II

Spring, 2022

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(under the auspices of Professor Antwan D. Clark)

Introduction

Mechanical ventilation (MV) has been widely used, where the goal is to stabilize the amount of oxygen to the body while also minimizing injuries to the patient's lung. The two primary modes of MV include the following.

1. Pressure Controlled Ventilation (PCV) – This mode of ventilation requires inputs of inspiratory pressure instead of tidal volumes. This form of ventilation allows the clinicians to control the maximal pressure.[1].
2. Volume Controlled Ventilation (VCV) – This mode of ventilation uses tidal volume and flow rate can be guaranteed and used as inputs.

Researchers have approached this topic from clinical and algorithmic perspectives, where processes have been proposed to clinically and automatically adjust the MV parameters based on patient data. However, these processes are limiting because they are patient specific and make more sporadic adjustments which is not conducive for a real-time clinical scenario.

The Solution

We propose a hierarchal deep reinforcement learning (HDRL) framework for mechanical ventilation for PCV consisting of the following aspects:

1. An intelligent agent (RL_Q) is proposed that adjusts the MV inputs while analyzing key properties of MV flow curve.
2. An intelligent agent (RL_{PV}) is proposed that manages RR and I/E MV for their targeted values.
3. A rules-based agent (RL_B) is proposed that supervises RL_Q , RL_{PV}, and RL_T.

The benefit to this approach is that this framework can perform robust monitoring and adjustment in much shorter time intervals than previous approaches that propose update changes every four hours. The results of this work can be extended to produce intelligent agents that not only help relieve constant monitoring by clinicians while also interacting with them and thus producing efficient, effective, and assured patient care.

Theoretical Development

Using the lung-mechanical ventilator model in MATLAB [1], we model these actions via the following Markov decision processes (MDPs).

The MDP (for RL_Q) is based of $\hat{Q} = \max |Q(t)|$ (for any PIP value).

- The state space $\boldsymbol{S_Q}$ – Based on the various heights of $\hat{Q}$ that correspond to variations of PEEP values.
- The action space $\boldsymbol{A_Q}$ – Based on increasing, decreasing, or not changing the PEEP values.
- The set of rewards $\boldsymbol{R_Q}$ – Based on the following schema:
  1. PEEP in operating range: $R_t = 20 - |PEEP - PEEP_{baseline}|$.
  2. PEEP not in operating range: $R_t = -80$.
  3. PIP in operating range: $R_t = 20 - |PIP - PIP_{baseline}|$.
  4. PIP not in operating range: $R_t = -80$.
  5. PIP = PIP_{tgt}: $R_t = 40$.
  6. IP in operating range: $R_t = 20$.
  7. IP not in operating range: $R_t = -80$.

The MDP (for RL_{PV}) includes the following [for any respiratory rate (RR)].

- The state space $\boldsymbol{S_{PV}}$ – Based on the total cycle time (TCT) based on T_{insp} and T_{exp}.
- The action space $\boldsymbol{A_{PV}}$ – Based on increasing, decreasing, or not changing the RR and I/E ratios.
- The set of rewards $\boldsymbol{R_{PV}}$ – Based on the following schema:
  1. RR in operating range: $R_t = 3 \times (20 - |RR - RR_{baseline}|)$.
  2. RR not in operating range: $R_t = -1000$.
  3. IE in operating range: $R_t = 30 - |IE - IE_{baseline}|$.
  4. IE not in operating range: $R_t = -1000$.
  5. RR = RR_{tgt}: $R_t = 90$. IE = IE_{tgt}: $R_t = 60$

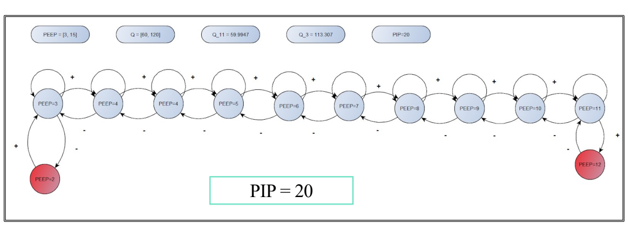

Fig. 1 An example MDP for RL_Q

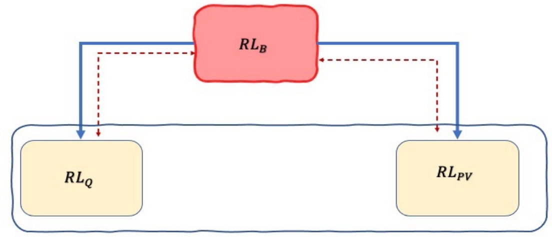

Fig. 2 Proposed HDRL Framework

Deep Q-Learning (DQN) was used to implement each of the subordinate agents in our HDRL framework. This consists of coupled neural networks (NNs), where a prediction network was used to predict each RL agent's moves followed by a target network to ensure that the RL agent reaches its targeted values.

Results

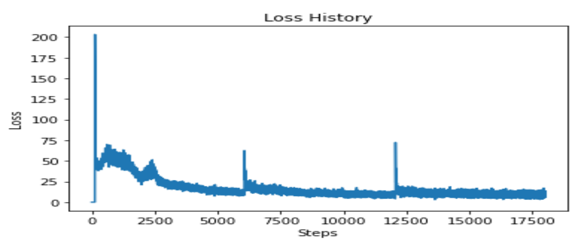

Fig.3 Loss History for RL_Q

Percentage of Achieved Targeted PIP Values for RL_Q [Target PIP = 25, Total Number of Occurrences = 273]			
Absolute Difference in Achieved PIP Value	Percentage of Occurrences	Percentage of Occurrences > Targeted PIP Value	Percentage of Occurrences < Targeted PIP Value
0	76.19	0	0
1	4.76	0	100
2 - 5	4.76	0	100

Future Work

An immediate area of future work includes finalizing RL_B via incorporating the outputs of RL_Q , RL_{PV}, and RL_T into this process where a framework has already been created.

References

1. M. Jaber *et al.* MATLAB/Simulink Mathematical Model for Lung and Ventilator, *32nd IEEE International Conference on Microelectronics (ICM)*, 2020.

Key Roles

Mr. Jiahe Xu: 1.) designed pressure-controlled mechanical ventilator with lung (MVL) mathematical model; 2.) performed data analysis on temporal output MVL responses to create the MDPs listed in the Theoretical Development Section.

Mr. Haoyu Shi: 1.) Built AI Gym environments from MDPs. Created and tested deep Q-Learning neural networks (DQNs) for RL_Q, RL_{PV}, and RL_T.

Acknowledgements

Special thanks to Dr. Clark for his mentorship and guidance.