Using ANNs in dynamical systems to improve asynchrony detection in mechanical ventilation

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Mechanical ventilation

Mechanical ventilation is used in Intensive Care Units (ICUs) to save lives of patients who are not able to breath on their own. Mechanical ventilation supports patients by ensuring adequate oxygenation and carbon dioxide elimination. Mechanical ventilators attached to the patient are used to ensure airflow in and out of the lungs. This is challenging for spontaneously breathing patients because it potentially leads to ventilators disrespecting the demands of the patient, i.e., Patient-Ventilator Asynchrony (PVA). Different types of PVA can be characterized based on the delay during inspiration Δt_{insp} and expiration Δt_{exp} between patient and ventilator. In practice, currently asynchronies can only be detected by real-time inspection of pressure and flow waveforms as depicted in Figure 1. However, clinicians lack time and/or knowledge to effectively detect asynchrony based on pressure and flow waveforms [1], therefore an automatic detection approach is pursued.

Detection problem

Using first principle modelling, it is found that PVA can be detected from pressure and flow curves based on nonlinear dynamical models with unknown parameters and logical rules that are patient and ventilator specific. From a system identification point of view, the goal is identify the dynamical models for a wide variety of plants (different patients) and inputs (available pressure and flow curves).

General approach

The general approach consists of experiment design, a model set choice and a fit criterion choice. In the experiment design, prior knowledge, in the form of first principle models, is used to generate synthetic data from a simulation environment. The set of models that we consider are artificial neural networks (ANNs). Subsequently, by choosing a fit criterion the dynamical model can be identified using the generated data and a particular model choice. In this way, the data-driven identified dynamical model contains implicit knowledge about the underlying first principle models. In case of the PVA detection, a dynamical model based on a recurrent neural network is trained using a cross-entropy loss function [2]. In the next section, the detection performance of the model is shown using synthetic patient data.

Results

Through a simulated case-study the performance of the detection model is shown in Figure 2. The figure shows all the different patient breaths represented by a single data point and their detected asynchrony type. The asynchrony type of a breath is detected correctly if the colour matches the background colour. The total detection accuracy is 93.3%, which is a significant improved compared to clinicians, which do often not have the time or ability to detect asynchronies in practice at all. In a larger context, this shows that data-driven models, such as ANNs, have the potential to represent complex dynamical systems if the models are trained with synthetic data that is generated with a first principle model-based simulation environment.

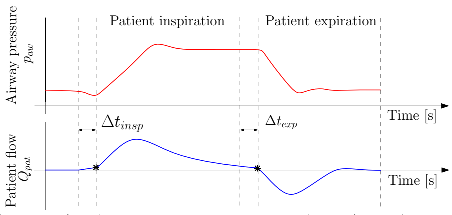

Figure 1: Typical pressure supported patient breath, where the ventilator supports the patient inspiration after Δt_{insp} seconds and cycles off Δt_{exp} seconds after the patient's expiration.

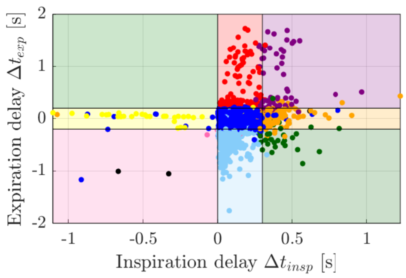

Figure 2: Results of the asynchrony detection model. Each data point represents patient breath combined with a ventilator breath that is characterized based on the inspiration delay Δt_{insp} and the expiration delay Δt_{exp}. An asynchrony is detected correctly if the data point has the same color as the background, which is the case for 93.3% of the breaths.

References

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