Noninvasive cuffless blood pressure estimation using pulse transit time-ECG monitor with photoplethysmography in pediatric patients

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INTRODUCTION

Arterial blood pressure (ABP) monitoring and management is important for children in the intensive care unit (ICU) or during surgical procedures. Continuous monitoring of ABP typically requires an invasive arterial catheter which brings risks of complications and limits its use to the sickest patients. Development of non-invasive, continuous methods for monitoring ABP would be beneficial for patients at risk for hypotension, but not ill enough to justify an invasive line.

Pulse transit time (PTT) is the difference in arrival time of a blood pulse wave reaching two different locations in the body and is inversely proportional to blood pressure.[1,2] In principle, PTT could be calculated from electrocardiogram (ECG) and photoplethysmography (PPG) signals from standard patient monitors, making ABP monitoring available to every patient. However, standard patient monitors were not designed to preserve the temporal relationship between ECG and PPG signals, complicating accurate estimation of ABP trends.

Objective

We are investigating the use of different machine learning models to estimate ABP from ECG and PPG waveforms from a large pool of patient monitor data and compare model predictions to invasive ABP.

MATERIALS AND METHODS

Study Design

This is a retrospective study of continuous patient monitor data (e.g. ECG, PPG, and ABP waveforms) of pediatric surgical patients with continuous invasive ABP monitoring in the operation room (OR) or intensive care unit ICU at Boston Children's Hospital between October 2020 to August 2021.

1. Moens et al. (1878), Korteweg et al., Ann Phys Chem (1878)
2. Gao M et al., Physiol Rep (2016)
3. Yang S et al., IEEE J Biomed Health Inform (2021)
4. Lin YT et al. PloS One (2019), Bennis F et al. PloS One (2019)

MATERIALS AND METHODS

Subjects

3342 patients were identified (mean [SD] age: 8.50 [9.68] years; weight: 28.84 [26.51] kg), 1929 of which were diagnosed with cardiovascular disease. Patient monitor data was extracted from data warehouse with Nihon Kohden. Datasets were filtered to those with > 30 minutes of ECG, PPG and ABP waveform data (Figure 1). Of those, the mean [SD] recording duration was 4.58 [3.40] hours.

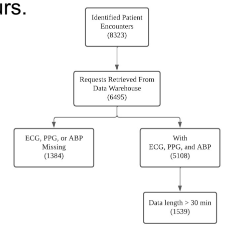

Figure 1. Data collection flowchart.

Data Processing

Data was pre-processed to remove artifacts. We extracted 35 features including PTT, heart rate, and various PPG shapes features, following the methods of Yang et al.[3] Four machine learning models were used to estimate ABP, including linear regression (LR), random forest (RF), feedforward neural network (FNN), and recurrent neural network (RNN).

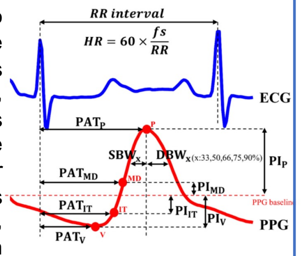

Figure 2. PTT Features (figure taken from Yang et al. [3]).

All data was processed on Python 3.7.3. The training of the RF model was using Scikit-learn library. Both FNN and RNN training were done using TensorFlow. Poincaré plots were generated by NeuroKit2.

RESULTS

We performed a preliminary subgroup analysis with data from the first eighty-six patients, comprising 1056451 heartbeats. Datasets were divided for training and testing by patient in an 8:2 ratio.

For the testing data sets, Figure 3 (upper) shows 2D histogram of model predicted ABP (ABP_pred) vs. measured invasive ABP (ABP_test). The mean ± SD difference between the model and actual ABP was -3.6 ± 8.8 mmHg for LR, -5.5 ± 9.6 mmHg for RF, -6.7 ± 14.1 mmHg for FNN and -9.4 ± 23.2 mmHg for RNN (Figure 3 lower).

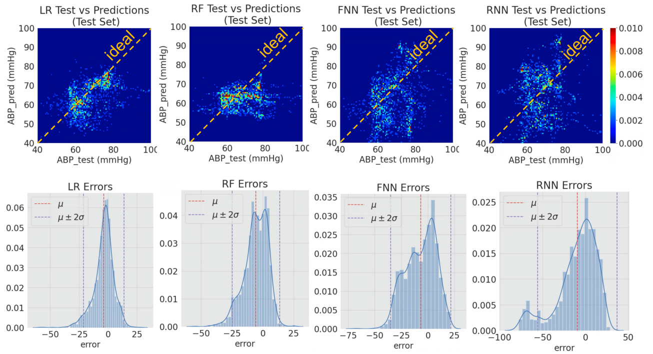

Figure 3. Testing and predicted data comparison (upper). Errors between testing and predicted data (lower).

DISCUSSION

- Among all tested models, the LR model had the best performance and the RNN had the worst.
- The main challenge is that patient monitor signals are heavily preprocessed within the monitor, distorting waveform features.
  - We also observed previously reported sawtooth artifact in PTT from relative time shifts in ECG and PPG waveforms (Figure 4).[4]
  - We tried adopting the methods of Yang S et al.[3] to include waveform shape information, independent of relative timing.
  - However, correlation analysis reveals RR intervals of the PPG waveform are distributed discretely, presumably from the monitor's internal processing of pulse oximeter signals (Figure 5).

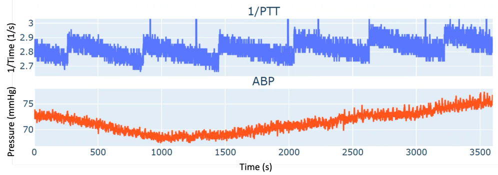

Figure 4. Sawtooth artifact in PTT

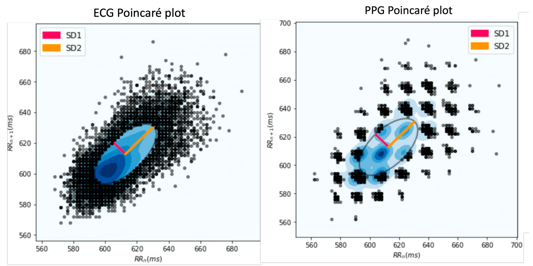

Figure 5. ECG and PPG Poincaré plots

Future Work

We plan to independently measure ECG and PPG signals simultaneously to obtain ground truth data. By comparing time-locked ECG and PPG waveform data with corresponding waveforms reported by the patient monitor, we hope to identify features which will improve performance of ML model prediction of ABP from standard patient monitor waveforms.