This project examines improvements to calibration-free blood pressure estimation using electrocardiogram (ECG) and photoplethysmography (PPG) signals. ECG is a voltage measure of the cardiac activity collected at the chest. PPG is an optical current measure of blood flow collected at the fingertip. The time delay from ECG-observed to PPG-observed heart beats has a theoretical nonlinear relationship [1] to blood pressure given sufficient per-subject parameterizations [2]. This project establishes a features space, assess various models, and demonstrates improvements to the previous work of [1].

The data [3] comprises 12000 sets of ECG, PPG, and blood pressure time-series sampled at 120Hz. Signal lengths are the same within a set but vary across sets. The ECG and PPG waveforms are the basis for the feature space. The invasively measured BP waveform provides computable targets for systolic, diastolic, and mean arterial (MA) blood pressure.

The models were assessed using three metrics drawn from British Hypertension Society [1] and RMSE. The results for each of the five models for MA, systolic, and diastolic pressure are respectively in tables 1, 2, and 3. The fifth model was the best performer for all three estimation problems and its results as compared to BHS standards and previous work [1] are in table 4.

### References


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### Data Segmentation

Generating relevant features and BP targets first requires isolating ECG R peaks and resulting PPG and BP wavefronts. This windowing process comprises several steps:

1. ECG Wavelet Transform (eq. 1) to enhance R peak features (fig. 1). S = 8.
2. K-Means filtering to isolate R peaks from all other signal maxima (fig. 1).
3. Outlier removal using RR interval detrending via weighted least-squares with RBF kernel (fig. 2).
4. Identification of resulting PPG waveform (fig. 3).
5. Identification of resulting BP wavefront (fig. 3).

Wavelet Operator:

\[
W(x, f) = \sum \phi(a, b) \left( x - \frac{a}{b} \right) \left( \frac{f}{b} \right)
\]

The models utilize twenty derived features comprised of three groups (fig. 4):

1. Subject's heart rate.
2. Time from R-Peak to PPG wavefront’s start.
3. Time from R-Peak to PPG wavefront’s end.
4. Time from R-Peak to PPG wavefront’s maximum slope.
5. Time from R-Peak to PPG wavefront’s peak.
6. Time from PPG peak to PPG inflection point.

- **PPG Signal Features to represent subject parameters:**
  7. Maximum slope of normalized PPG waveform.
  8. Area under normalized PPG signal between start and maximum slope.
  9. Area under normalized PPG signal between maximum slope and peak.
  10. Area under normalized PPG signal between peak and inflection point.
  11. Area under normalized PPG signal from inflection point to the end.

- **PPG Integral Quantities to represent subject parameters:**
  12-20. The time for PPG integration to reach 10, 20, ..., and 90 percent of total integration.

The three blood pressure targets are defined as:

1. Systolic pressure is the maximum value of a BP wave segment.
2. Diastolic pressure is the value at the end of the BP wave segment.
3. MAP is the mean pressure of the BP wave segment.

### Results

### Discussion

The results demonstrate a marked improvement on previous work [1]. It is difficult to compare exactly as they reported using 4254 records and it remains ambiguous if this of the 12000 data sets or the number of feature epochs. Due to computational limitations, this project used the first 3000 of the 12000 data sets that after filtering resulted in 604,052 feature epochs.

Perhaps the most interesting outcome is that the models uniformly estimated diastolic pressure better than systolic pressure. Thus, MA pressure estimation expectedly was the middle performer. Commercial viability will rely on improving systolic estimation.

### Future Work

The models’ performance needs to increase to obtain a BHS grade A rating. Because test and training errors are respectively low, the models likely suffer from high bias due to fewer and/or weaker features. This bias and the time-series nature of the data inspire applying CNN’s and/or recurrent activations for their automated feature learning and expressive power.