Report On

Cuffless Blood Pressure estimation algorithms using ECG and PPG signals

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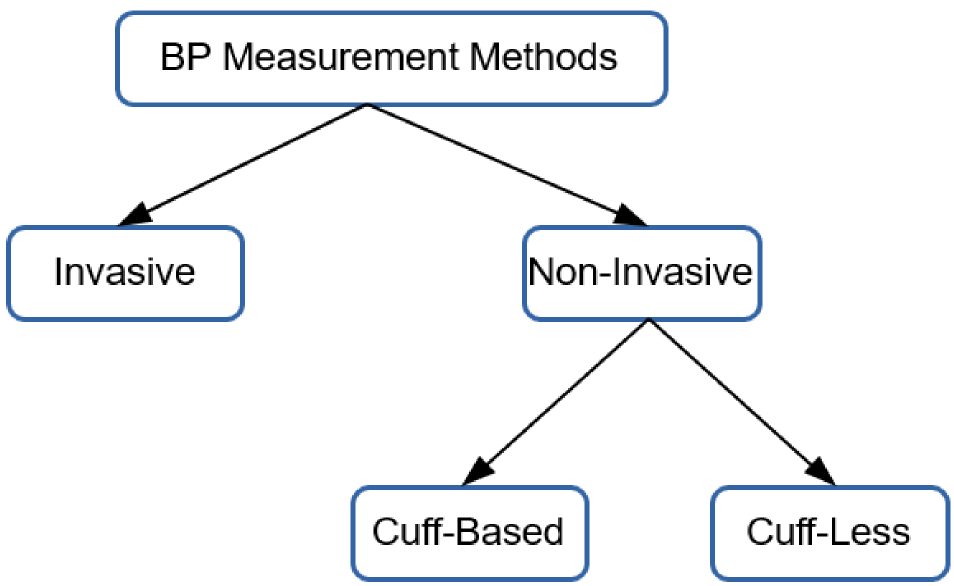
Based On

Kachuee, Mohammad & Kiani, Mohammad Mahdi & Mohammadzade, Hoda & Shabany, Mahdi. (2016). Cuff-Less Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring. IEEE Transactions on Biomedical Engineering. 64. 1-1.

Introduction

According to the World Health Organization, the prevalence of hypertension in men and women is 24% and 20.5%, respectively. Hypertension occur when BP is higher than normal. Unluckily, most of the hypertension patients are not aware of their illness, while it damages their internal body organs silently (e.g., brain, eyes, kidneys, and viscus), which is why it is called the silent killer. Continuous blood pressure (BP) measurement is necessary, for accurate diagnosis and treatment of hypertension. BP is a periodic signal with the heart rate (HR) frequency that is normally bounded in a limited range. BP is the pressure which is applied to vessel walls, measured in mmHg. The BP blows among maximum and minimum values, which are called systolic blood pressure (SBP) and diastolic blood pressure (DBP), correspondingly.

BP Measurement Methods



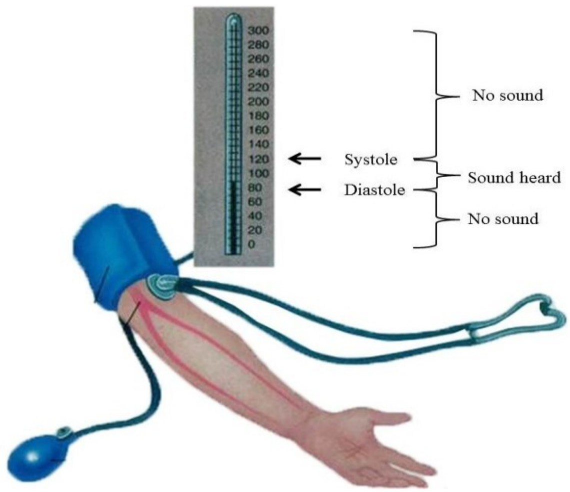
Invasive BP Monitoring

Invasive (intra-arterial) blood pressure (IBP) monitoring is a frequently used method in the Intensive Care Unit (ICU) and is also often used in the operating theatre. This technique includes direct measurement of arterial pressure by injecting a cannula needle in a suitable artery. The cannula must be connected to a sterile, fluid-filled system, which is connected to an electronic patient monitor. The advantage of this system are: accurate BP values by direct measurement and continuous and instantaneous BP. Disadvantages are: Requires surgery to implement a pressure sensor, and need sterilized conditions.

Non- Invasive BP Monitoring

Cuff-Based

Non-Invasive very precise and traditional measurement technique, that use mercury sphygmomanometer. In this technique, a nurse wraps an expandable cuff around the patient's arm and inflates it. Disadvantages: Inconvenient and Dis-continuous method for BP measurement.



Cuff-less

The main of goal of this paper is continuous BP monitoring with cuff-less method. Advantages are below:

- Non-Invasive
- Convenient
- Continuous

Disadvantages:

- Requires Calibration
- No established Standard

BP Measurement Challenges

There are some BP measurement challenges such as

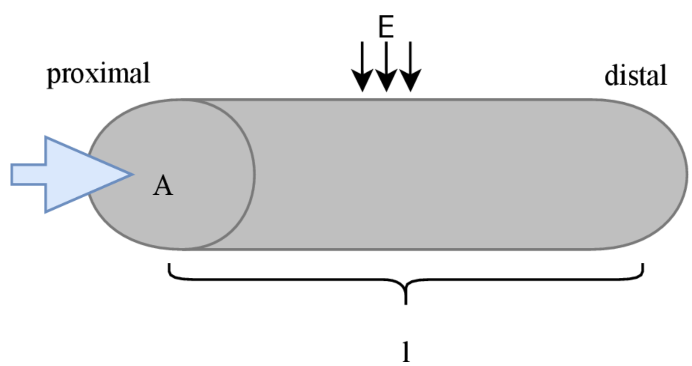
- Capability of continuous BP monitoring Indirect calculation of BP
- Subject specific parameters
- Evaluation using established health standards Health design considerations

Background

BP and PTT relationship

The vascular system can be demonstrated as connected elastic tubes in which the blood flows.

Elastic tube model

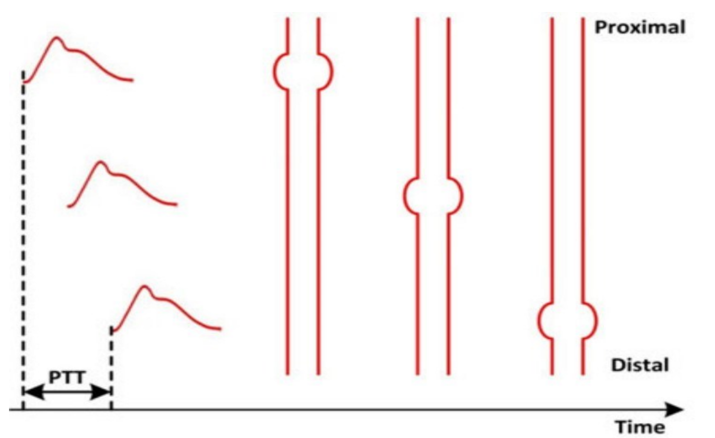


Wave Propagation in Arteries

Propagation of the pressure wave in the vascular system can be modeled by the propagation of a pressure wave inside tubes that have mechanical properties similar to arterial walls.

Pulse Transit Time (PTT)

A pressure wave propagates from the proximal end through the tube, and reaches the distal end after a time interval, called PTT.



Equations

Compliance equation,

$$C(P) = \frac{A_m}{\pi P_1 \left[1 + \left(\frac{P - P_0}{P_1}\right)^2\right]}$$

Wave propagation

$$P(x,t) = f\left(x \pm t/\sqrt{LC(P)}\right)$$

Wave Velocity

$$\mathbf{PTT} = l\sqrt{LC(P)}.$$

PTT-BP relationship

$$\mathbf{PTT} = l\sqrt{\frac{\rho A_m}{\pi A P_1 \left[1 + \left(\frac{P - P_0}{P_1}\right)^2\right]}}.$$

Vital Signals

- Arterial Blood Pressure (ABP)
- Electrocardiograph (ECG)
- Photoplethysmograph (PPG)

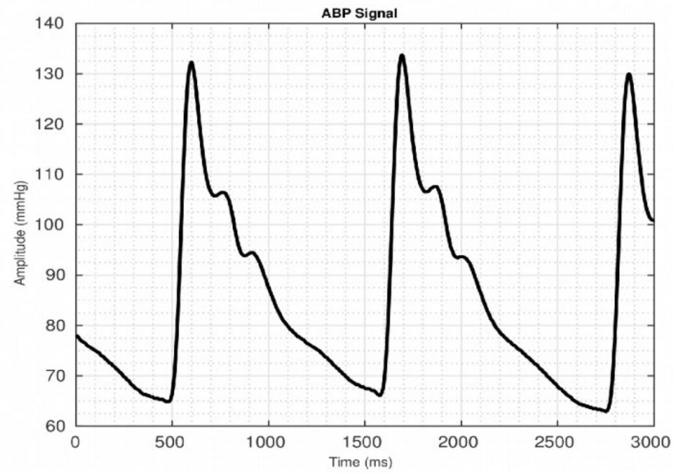
Arterial Blood Pressure (ABP)

Instantaneous BP signal

Invasive measurement method (Radial Artery Catheterization)

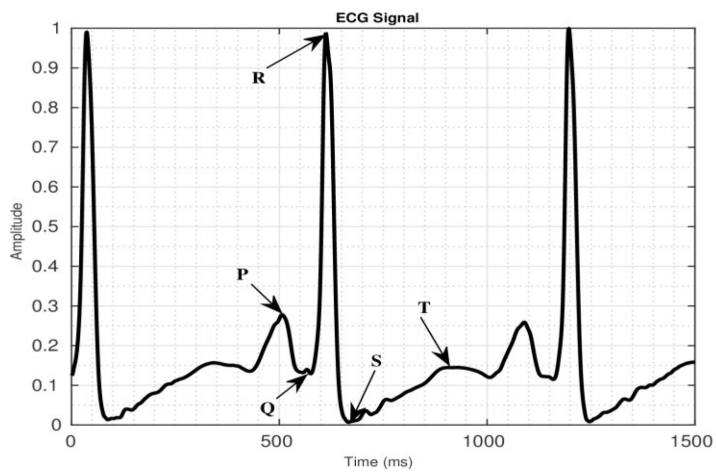
Here, it is used as target

- SBP = ABP maximum
- DBP = ABP minimum
- MAP = (SBP+2*DBP)/3



Electrocardiograph (ECG)

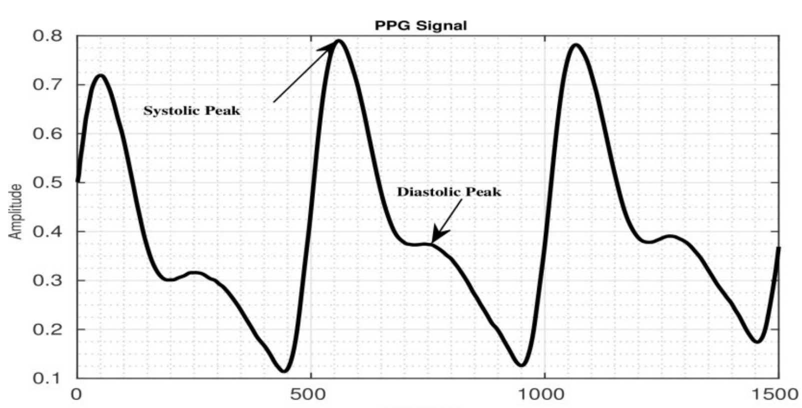
Recording the electrical activity of the heart by closing an electrical circuit loop inside the body.



Photoplethysmograph (PPG)

Photoplethysmograph = photo + plethysmos + graph

Recording changes of the blood volume



Proposed Methodology

Bellow figure shows the basic block diagram of the proposed cuffless BP estimation algorithm in this paper, which consists of the following steps:

1) Buffering the ECG and PPG signals as the primary inputs of the algorithm,

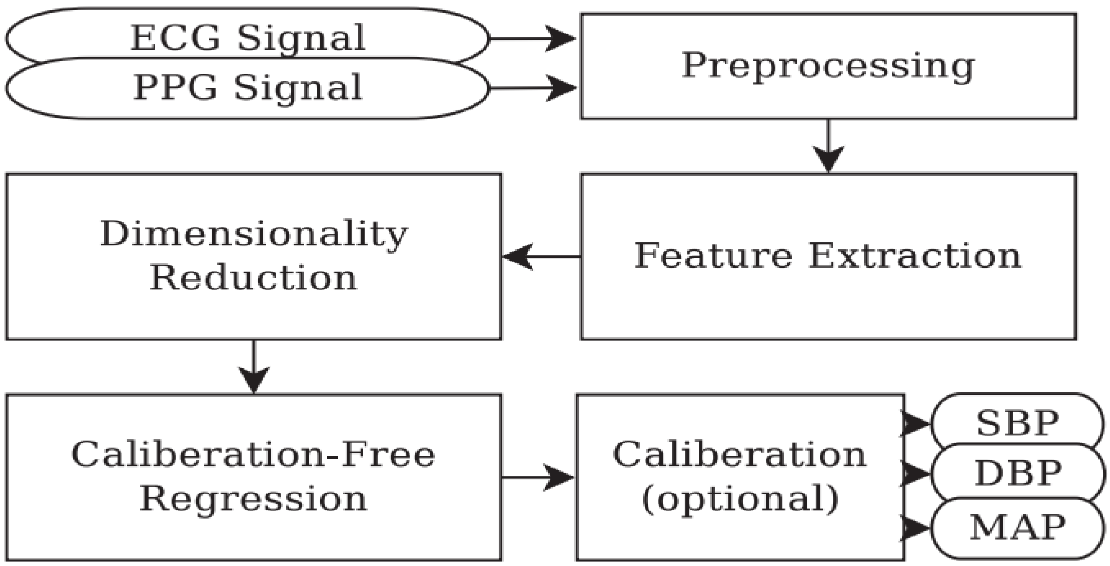
2) Preprocessing the ECG and PPG signals consisting of removing artifacts and deniosing,

3) Extraction of informative features from the preprocessed signals,

4) Reduction of the dimension of the extracted features,

5) Calibration-free regression, and finally,

6) An optional calibration step.



Block diagram of the proposed cuff-less BP estimation method.

Preprocessing

Noise and artifacts:

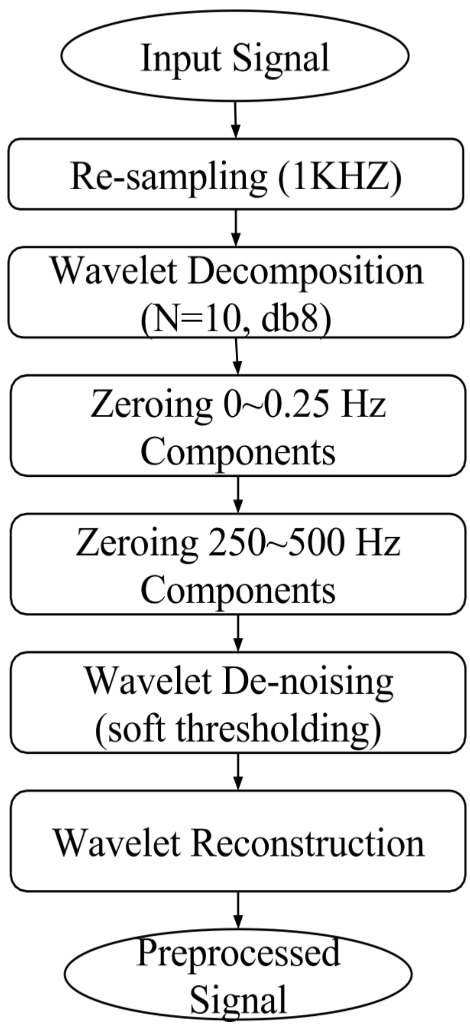
- Power-line 50 or 60 Hz noise
- Baseline wandering (low frequency)
- Muscle activity artifacts (high frequency, non-stationary)

Filtering and De-noising methods

- Frequency selective filtering (FIR, IIR, etc.)
- Discrete Wavelet Transform (DWT)

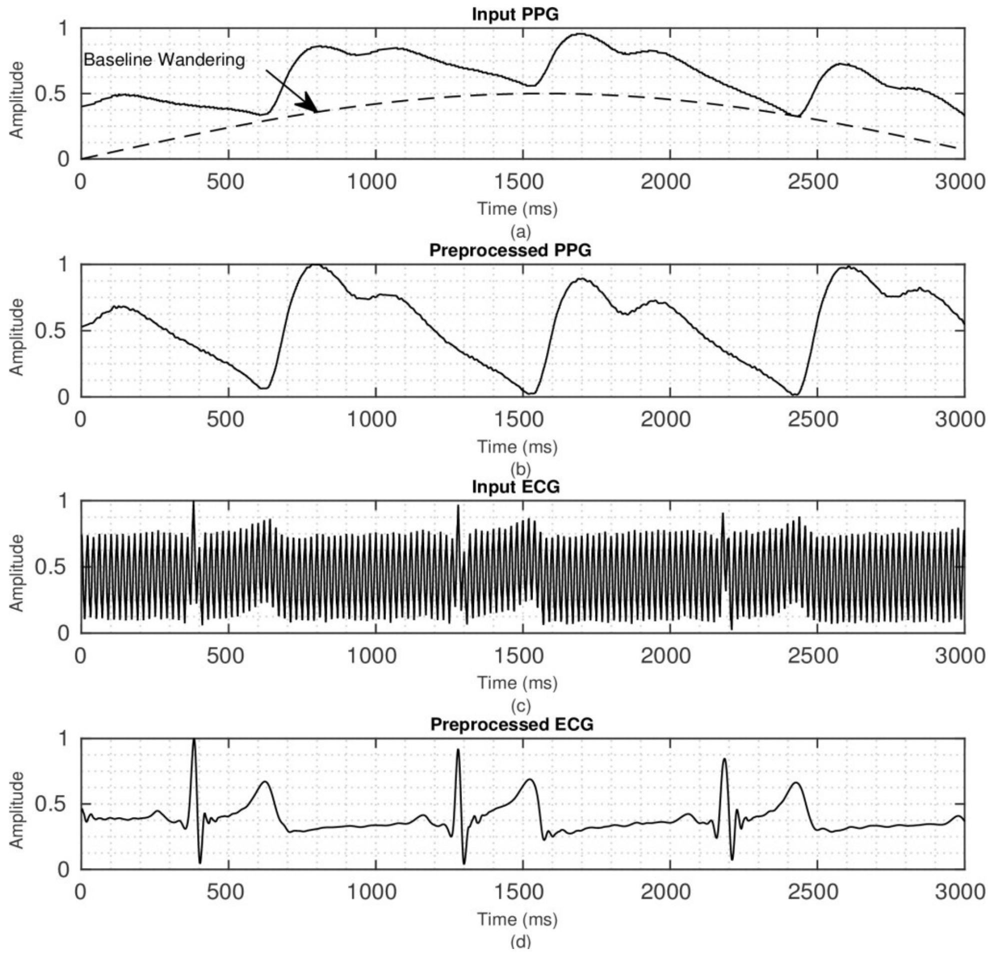
Preprocessing: Pipeline

Bellow figure shows the preprocessing pipeline of the ECG and PPG signals.

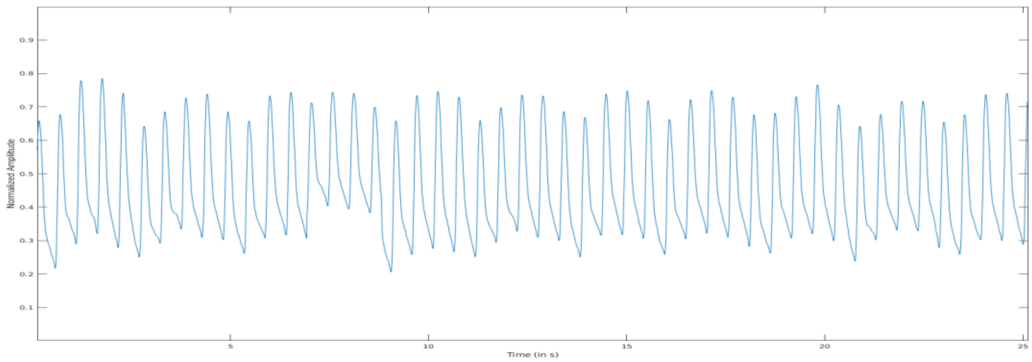


In order to make the following parts invariant to the probable changes of the sampling frequency of the input signals, this block first resamples inputs at a fixed frequency of 1 kHz, which is equal to the high-resolution ECG sample rate. Afterwards, the signal is decomposed by means of the DWT with the Daubechies 8 (db8) mother wavelet and to ten decomposition levels. Then, the components corresponding to the very low-frequency range of 0–0.25 Hz and ultrahigh frequencies between 250 and 500 Hz are eliminated by zeroing their decomposition coefficients. The conventional wavelet de-noising is performed on the remaining decomposition coefficients with soft Rigrsure thresholding strategy. Finally, cleaned signal is recovered by the reconstruction of the decomposition.

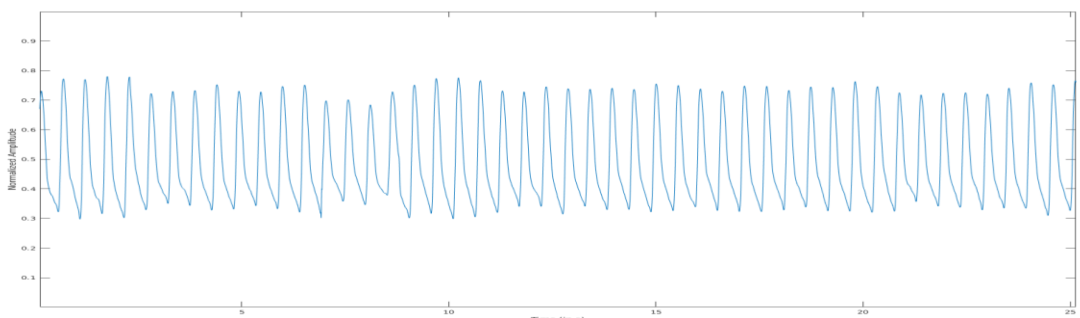
Preprocessing: Example



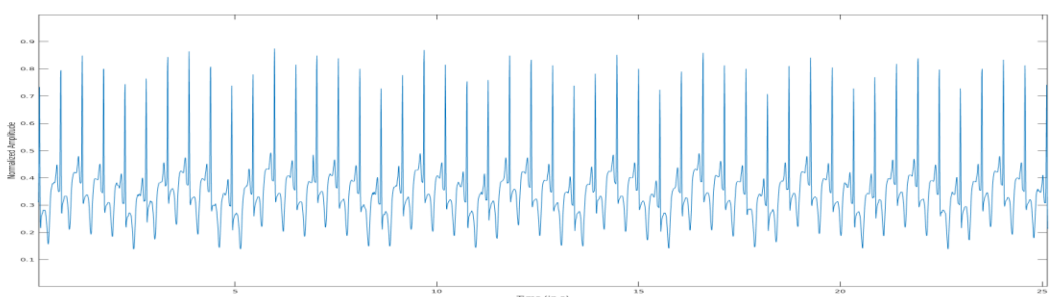
Our Pre-processing Result



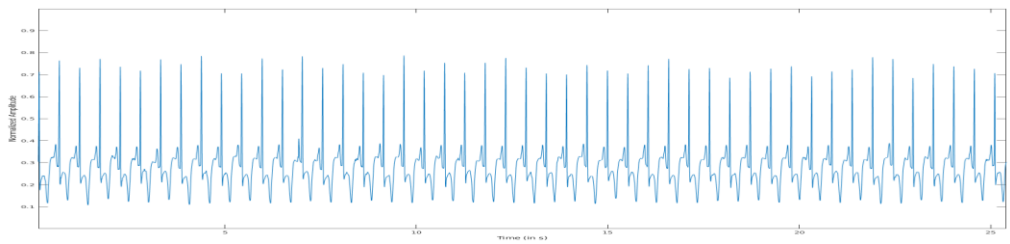
Input PPG Signal

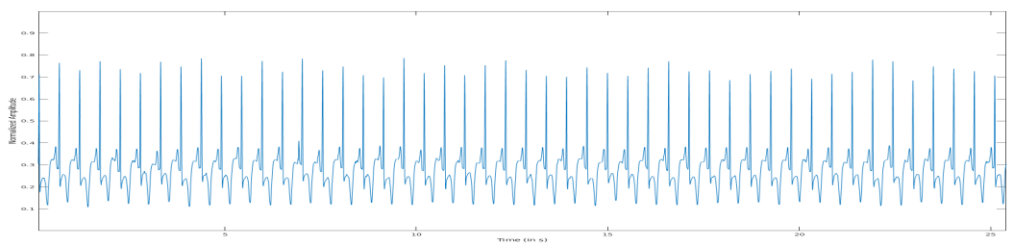


Preprocessed PPG Signal



Input ECG Signal





Preprocessed ECG Signal

Feature Extraction Methods

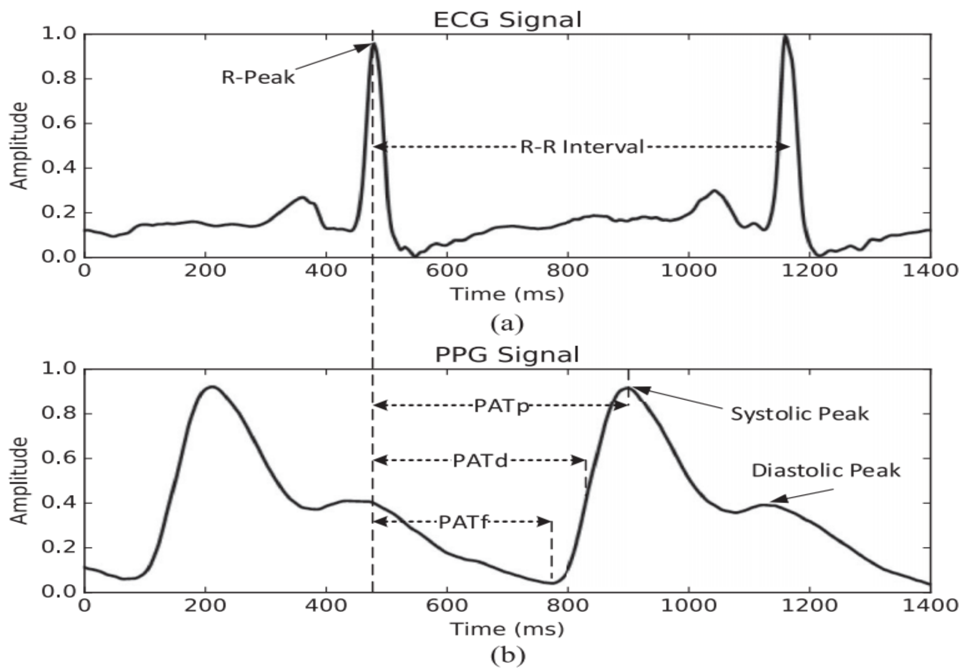
Parameter-Based

- Based on physiological parameters PTT features + PPG shape features
- Small feature vector length
- Limited by the signal morphology

Whole-Based

- Whole-based representation of signals
- Fully automated feature extraction and selection
- Works on almost every valid signal
- Large and complex feature vectors

Parameter-Based



Figure(a) representing PAT features and figure(b) showing Heart Rate (HR) features.

Augmentation Index (AI)

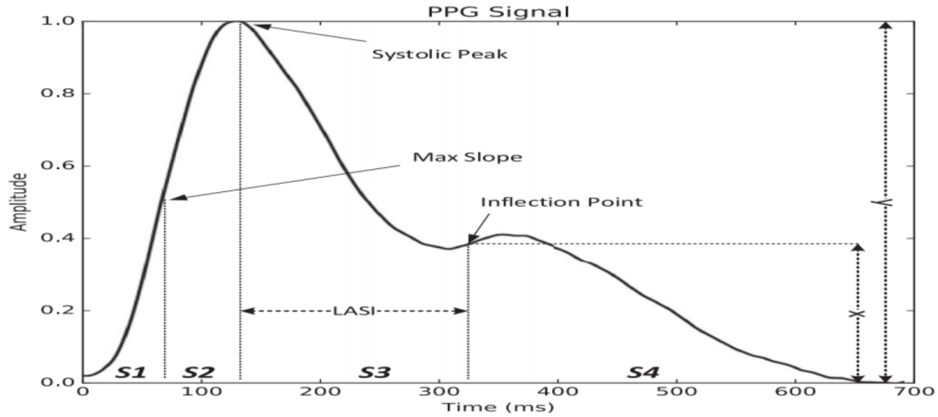
- A measure of wave reflection
- AI = x / y

Large Artery Stiffness Index (LASI)

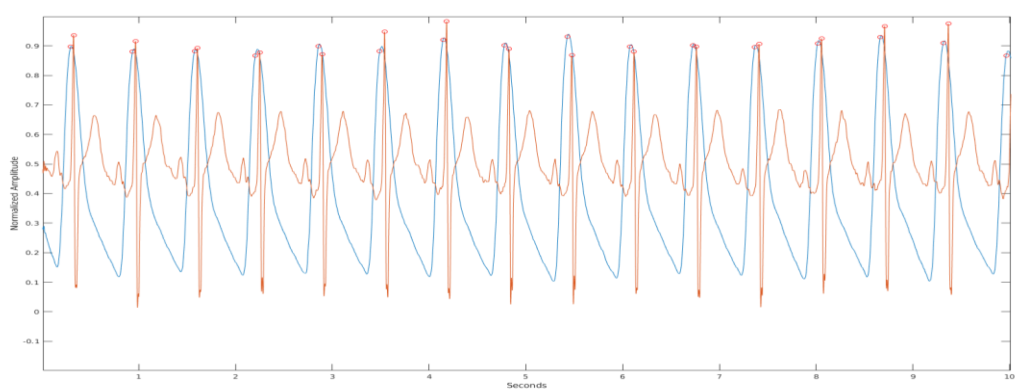
- Indicator of arterial stiffness

Inflection Point Area (IPA)

– Area S1, S2, S3 and S4 as shown in figure

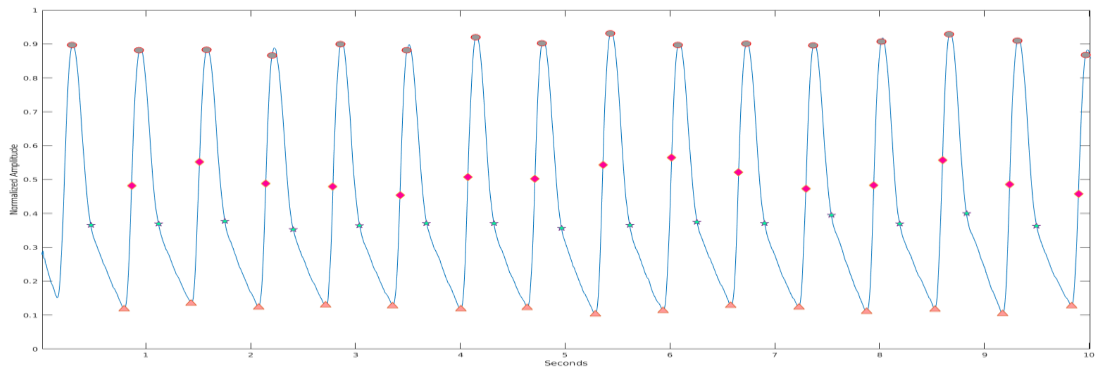


ECG Signal



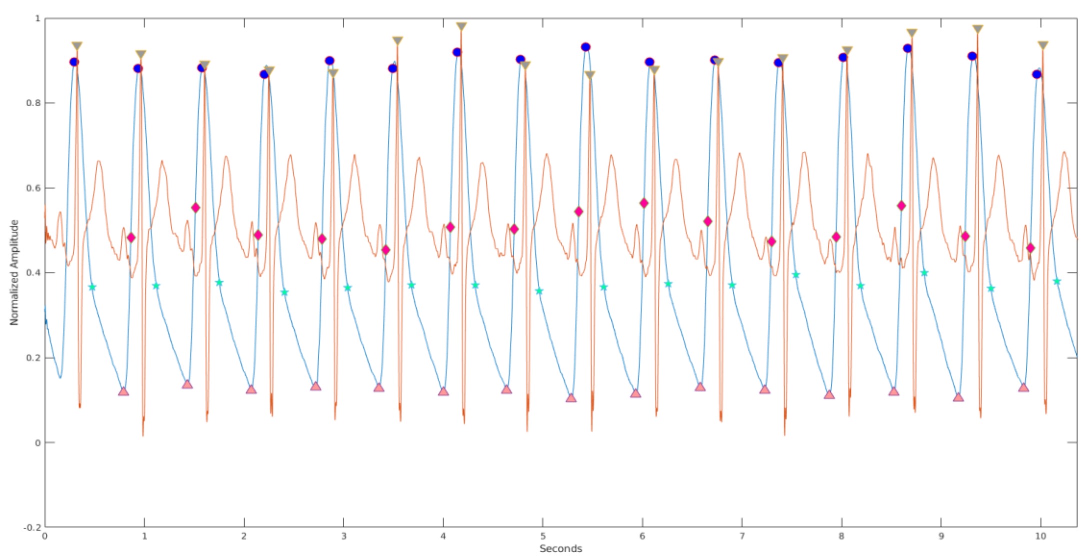
Red Curve: ECG, Blue Curve: PPG, and Re Circles corresponding peaks.

PPG Signals



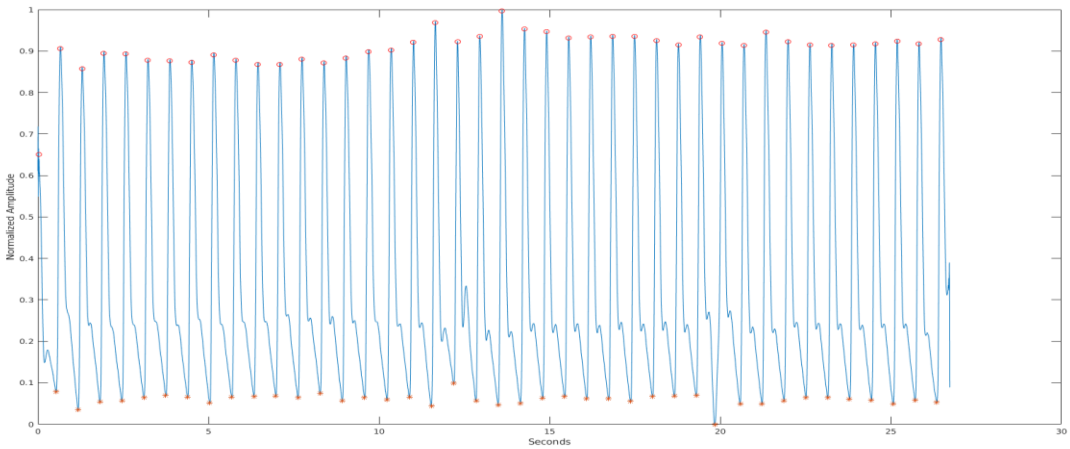
Circle: Systolic Peaks, Triangles: Diastolic Peaks, Diamonds: Max slope points, and Stars: Inflection Points.

Combined PPG-ECG plot with features identified



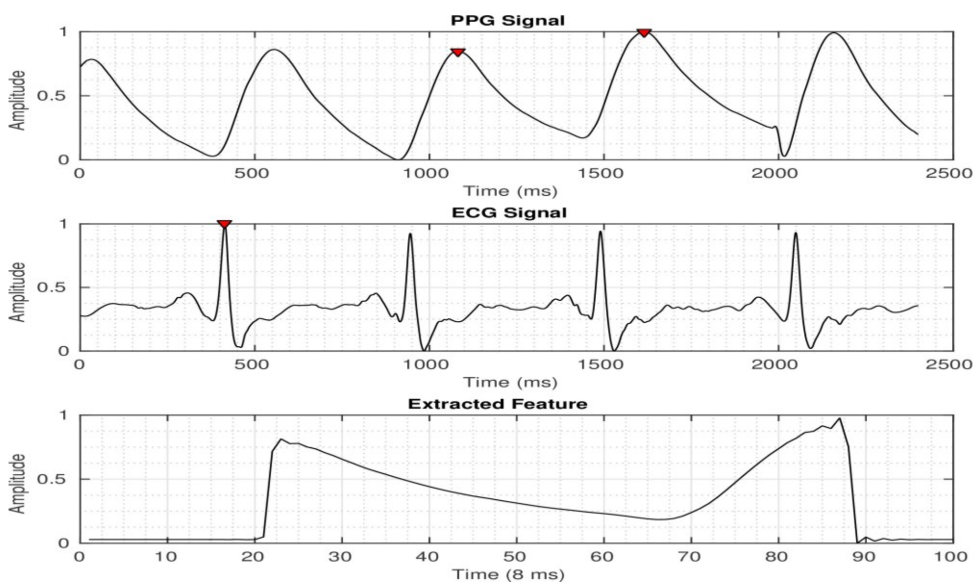
Circles: Systolic Peaks Triangles: Diastolic Peaks Diamonds: Max slope points Stars: Inflection points.

ABP Signal with SBP and DBP identified

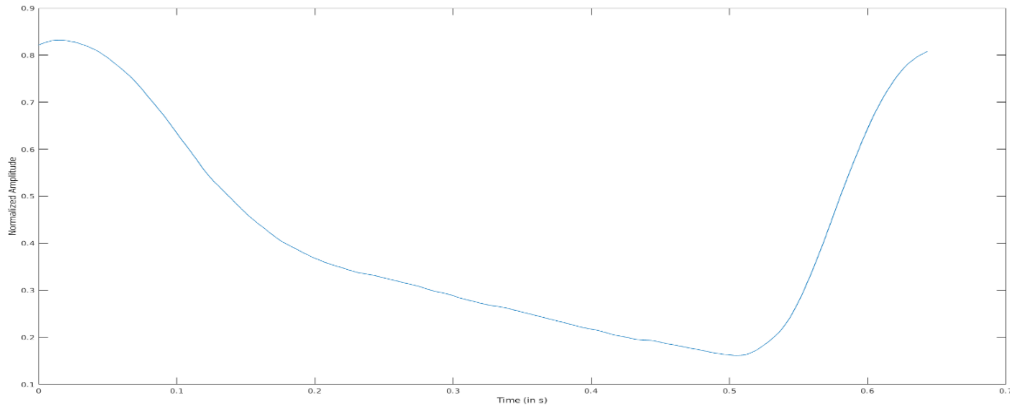


Circles: SBP* Asterisk: DBP* *Normalized

Whole Based



- PPG waveform between two Systolic peaks.
- Systolic peaks at distance greater than or equal to mean PATp from R-peak are selected.



Whole Based Feature, extracted using PPG signal

Training Validation and Testing

Experiment setup

IDE: MATLAB 2018b

Environment: Windows 10、Intel i5、NVIDIA 940MX

Features in experiment

We split 3000 samples into 3 one-third datasets. Once eliminated the abnormal samples, there are 994 in training set, 978 in validation set, 984 in test set.

As mentioned above, we have the parameter-based features and whole-based features. Parameter-based features are m by 12 matrix containing feature columns namely PATp, PATf, PATd, HR, augindx, LASI, S1, S2, S3, S4, SBP and DBP in sequential order, where SBP and DBP are our target variables.

Whole-based features are m by 15 matrix, which is the top 15 PCA components.

Regression Algorithms

We use the same algorithms in the paper:

1. **Linear Regression**

2. **Regression Tree** (Decision Tree using regression in MATLAB)
3. **SVM** (Support Vector Machines)
4. **LSBoost** (Least Square Boosting)
5. **Random Forest**

Linear Regression

It is well known that the final trained models are not applicable when the feature vector and the target have a strong nonlinear relationship. However, they are simple, easy to train, less prone to overfitting, and, compared to other alternatives, require less training samples, and hence, they are more efficient, which makes their implementation more efficient.

Regression Tree

Decision trees build models in the form of a tree structure, which consists of a number of decision nodes that each selects a branch based on a trained condition. An input traverse decision nodes of a tree to a leaf node which determines the final prediction value. Decision trees are models which are easy to understand and interpret. However, in some problems, they can create over-complex structures that do not generalize well, and hence demonstrate a poor performance.

SVM (Support Vector Machine)

SVMs are among the most powerful learning algorithms in terms of creating strong models with a reasonable training effort and a high noise tolerance. SVM regression is considered a nonparametric technique because it relies on kernel functions.[1]

LSBoost (Least Squares Boosting)

LSBoost fits regression ensembles. At every step, the ensemble fits a new learner to the difference between the observed response and the aggregated prediction of all learners grown previously. The ensemble fits to minimize mean-squared error.[2]

Random Forest

Random forests are ensemble learning methods in which the final prediction is created by combining predictions from a number of weak learners (e.g., decision trees). For the sake of having a low bias and a reasonably low-prediction variance, each tree is trained on a random subset of the training data. In a regression problem, the final prediction of a random forest model is the average of the predictions by each regression tree.

Hyper-parameter optimization

Hyper-parameter optimization in MATLAB is similar to the grid search in Scikit-learn. It tries different algorithms'parameter compositions to achieve lowest objective function specified by ourselves without manually tuning all the parameters. In this case, we do not try all of the possible compositions; instead, use some of them to reduce training time.

Note: There is no cross validation involved in any of the algorithms used above, though, hyper-parameter tuning is used.

Experiment Results

The table below shows our results.

	SBP				**DBP**			
Feature	Parameter-based		Whole-based		Parameterbased		Whole-based	
Metric	MAE	STD	MAE	STD	MAE	STD	MAE	STD
Linear Regression	21.8529	13.8757	22.7649	14.5258	9.2375	8.2620	9.6582	7.7014
Regression Tree	24.5833	16.4895	25.3302	17.0232	**8.6479**	7.5251	8.9634	**7.2748**
SVM	25.2589	16.8740	25.2589	16.8740	8.9241	**7.2994**	**8.9241**	7.2994
LSBoost	**19.5847**	13.1805	22.5400	**14.4620**	9.2859	7.9595	9.5283	7.6226

Random Forest	19.5951	**13.0232**	**22.5165**	14.5328	9.0530	7.5888	9.7610	7.5858

LSBoost takes the first place when evaluated in terms of parameter-based MAE on SBP signal.

Random Forest takes the first place when evaluated in terms of whole-based MAE on SBP signal

Regression Tree takes the first place when evaluated in terms of parameter-based MAE on DBP signal.

SVM takes the first place when evaluated in terms of whole-based MAE on DBP signal.

Paper result

TABLE II
COMPARISON OF THE PERFORMANCE USING THE TWO FEATURE SETS AND VARIOUS LEARNING ALGORITHMS

	Systolic Blood Pressure (mmHg)				Diastolic Blood Pressure (mmHg)			
Feature Set	Parameter-based		Whole-based		Parameter-based		Whole-based	
	MAE	STD	MAE	STD	MAE	STD	MAE	STD
Linear Regression	14.71	10.79	14.14	10.44	6.74	6.11	6.75	6.12
Decision Tree	16.28	16.28	17.15	14.97	7.75	8.54	8.44	9.17
Support Vector Machine	12.26	10.32	12.65	10.33	5.91	5.78	6.19	6.07
AdaBoost	**11.17**	10.09	**11.87**	10.30	**5.35**	6.14	**5.78**	6.61
Random Forest	11.80	**9.87**	12.39	**10.09**	5.83	**5.71**	6.39	**6.06**

Limitations

- Some of the PPG, ECG and ABP signals are very noisy. Such noise could not be removed by conventional preprocessing.
- The dataset we use for learning is relatively small compared to other Machine learning studies as well as the ones used in the paper. Also, we calculate the median waveform from one record in PPG, ECG, further reducing the sample size of our data.

Discussion

- To improve the accuracy, we can manually check the waveforms during training for large noise and remove them,
- Also, we can add more data during learning phase from different individuals.
- Calibration of extracted features can also improve accuracy.
- It may be possible to extract more features from PPG and ECG signals for better estimation of SBP and DBP.
- We could try neural network or different algorithms.

Conclusion

Our results indicate that cuffless blood pressure estimation using ECG and PPG signals is feasible within bounds of error even with this relatively low data records.

References

[1] "Understanding Support Vector Machine Regression - MATLAB & Simulink." [Online]. Available: https://www.mathworks.com/help/stats/understanding-support-vector-machine-regression.html. [Accessed: 14-Jan-2019].

[2] "Ensemble Algorithms - MATLAB & Simulink." [Online]. Available: https://www.mathworks.com/help/stats/ensemble-algorithms.html#bsw8av_. [Accessed: 14-Jan-2019].