

Design of Efficient Algorithms for Cuff-less and Continuous Estimation of Blood Pressure in Smart Mobile Healthcare Systems

Mohammad Kachuee

Jul 2016

Outline



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → Hardware Implementation
- **→** Conclusion

Blood Pressure (BP)



- The pressure which is applied to vessel walls
- Measured in mmHg

Hypertension

- Hypertension occurs when BP is higher than normal
- Prevalent among 24% and 20% of men and women, respectively
- Called the silent killer

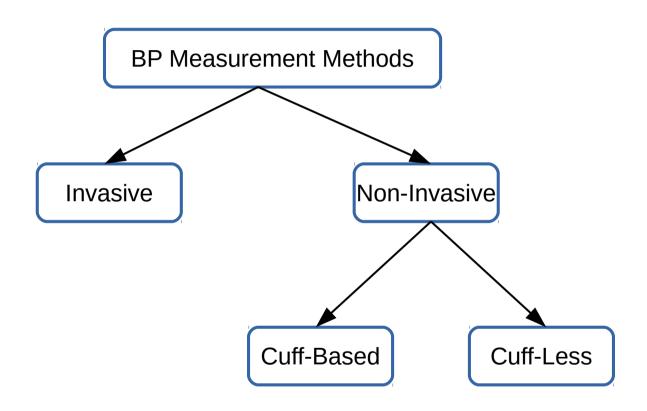
Outline: BP Measurement Methods



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → Hardware Implementation
- → Conclusion

BP Measurement Methods





BP Measurement Methods: Invasive



- ✓ Accurate BP values by direct measurement
- ✓ Continuous and instantaneous

- X Requires surgery to implement a pressure sensor
- X Requires sterilized conditions

BP Measurement Methods: Non-Invasive

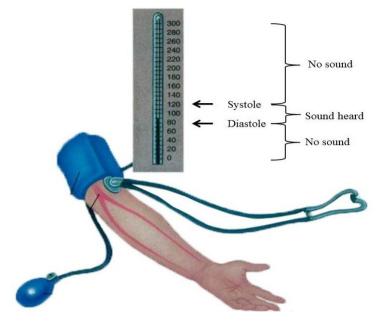


Cuff-based

- ✓ Non-invasive
- established standards
- x Inconvenient
- x Discontinuous

Cuff-less

- ✓ Non-invasive
- Convenient
- Continuous
- x Requires Calibration
- x No established standard



(Image from www.fastbleep.com)

BP Measurement Challenges



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

Outline: Background



- → Blood Pressure
- → BP Measurement Methods
- → <u>Background</u>
- → Proposed Methodology
- → Results
- → Hardware Implementation
- → Conclusion

Background



BP and PTT relationship

Wave propagation in arteries

Vital signals

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

Background: Wave Propagation in Arteries

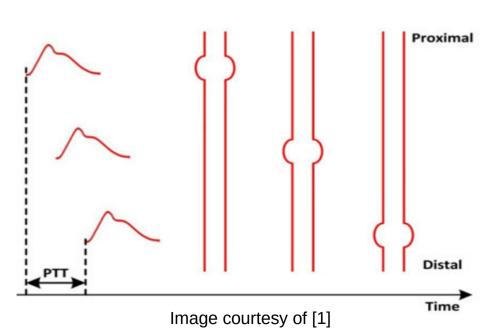


• Elastic tube model:

proximal distal

A

• Pulse Transit Time (PTT):



Background: Wave Propagation in Arteries



Compliance
$$(\frac{\partial A}{\partial P})$$

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

Wave propagation (see [17])

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

Wave velocity

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

PTT-BP relationship

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

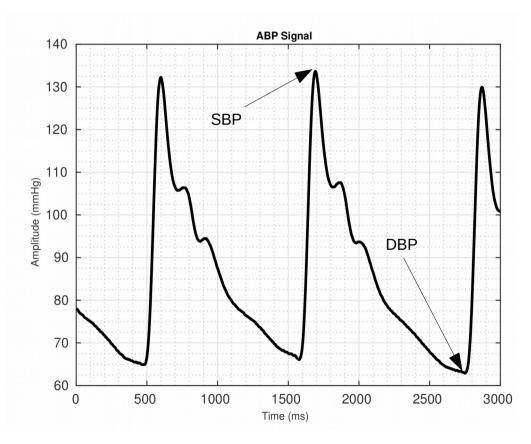
Vital Signals: ABP



- Instantaneous BP signal
- Invasive measurement method (Radial Artery

Catheterization)

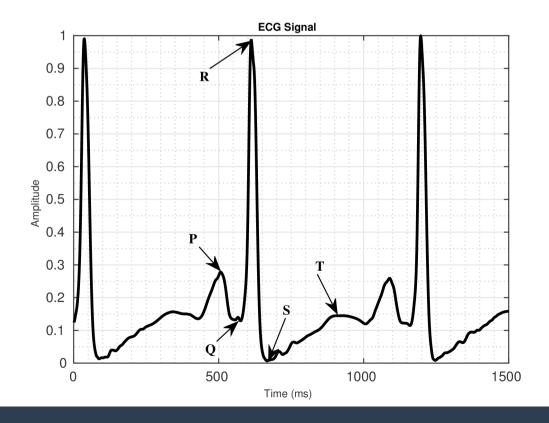
- Here, it is used as target:
 - SBP = ABP maximum
 - DBP = ABP minimum
 - MAP = (SBP+2*DBP)/3



Vital Signals: ECG



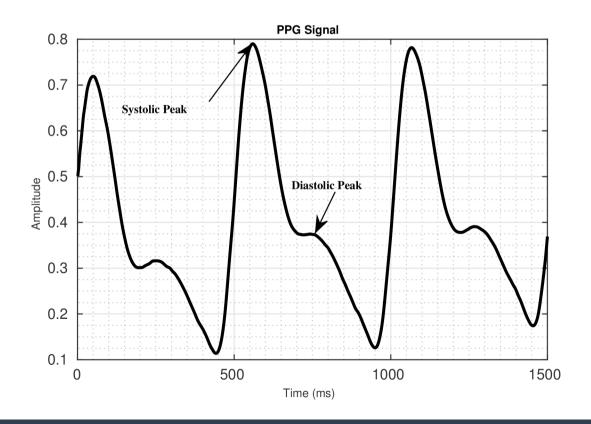
- Electrocardiography (ECG or EKG)
- Recording the electrical activity of the heart by closing an electrical circuit loop inside the body



Vital Signals: PPG



- Photoplethysmograph = photo + plethysmos + graph
- Recording changes of the blood volume



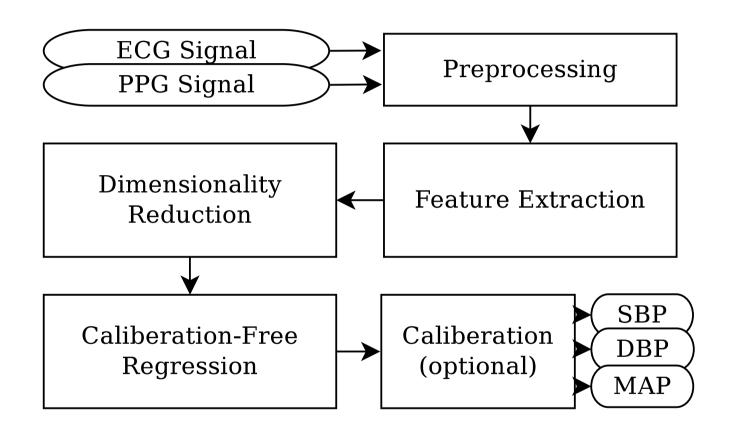
Outline: Proposed Methodology



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → Hardware Implementation
- → Conclusion

Proposed Methodology





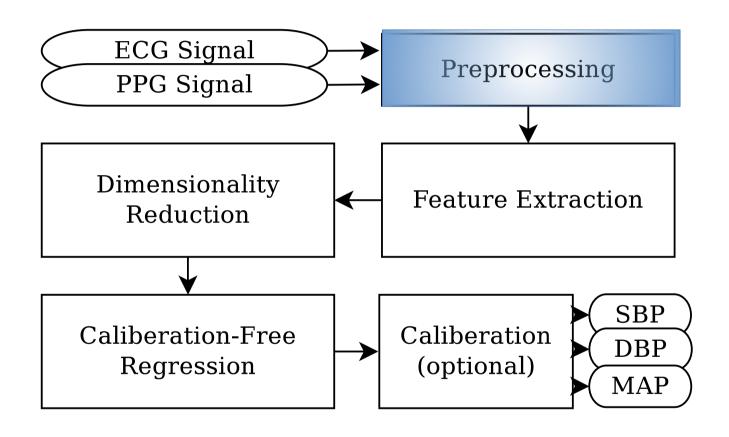
Data Collection



- Multi-parameter Intelligent Monitoring in Intensive Care (MIMIC) II:
 - Online database at <u>physionet.org</u>
 - Consists of terabytes of medical records
 - Data is collected from ICU patients

Proposed Methodology: Preprocessing





Preprocessing: Noise and Artifacts



Noise and artifacts:

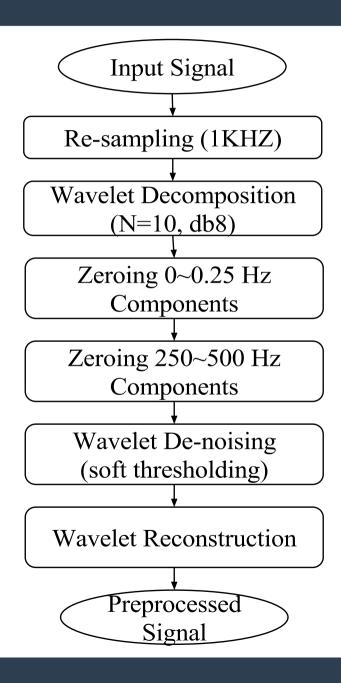
- Power-line 50 or 60 Hz noise
- Baseline wandering (low frequency)
- Muscle activity artifacts (high frequency, non-stationary)

Filtering and denoising methods:

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

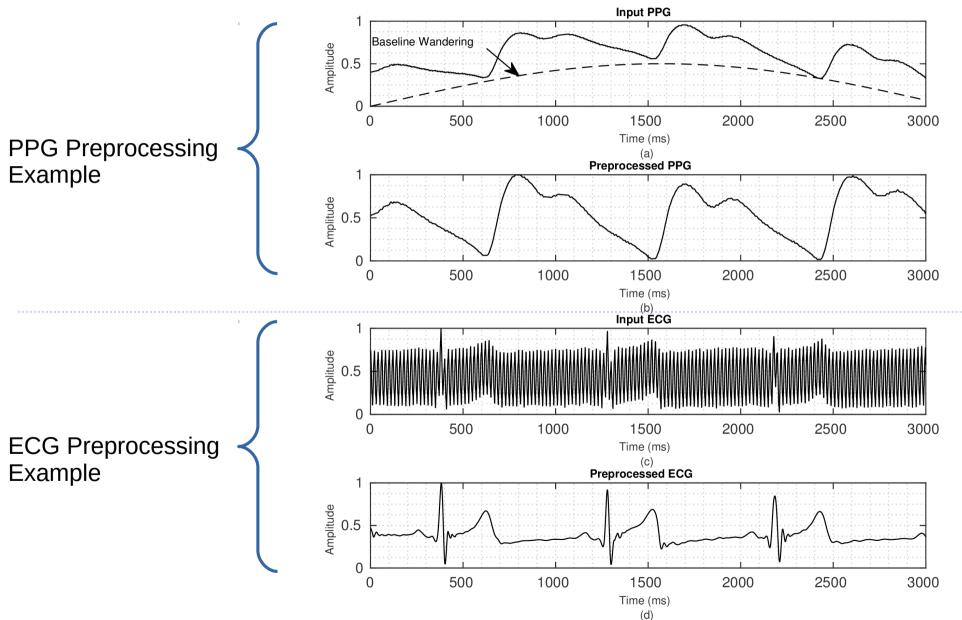
Preprocessing: Pipeline





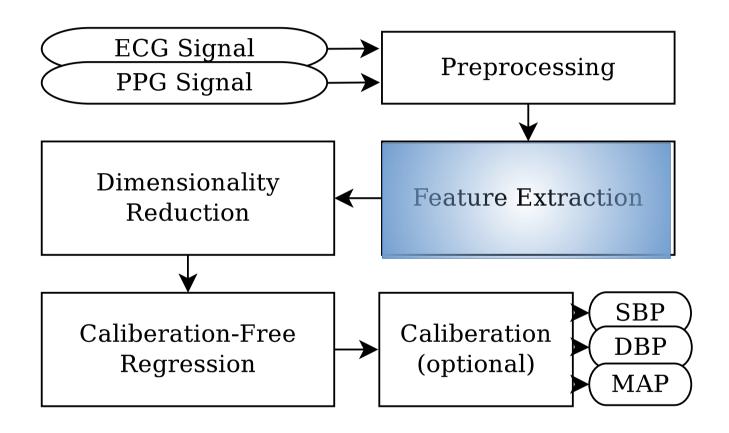
Preprocessing: Example





Proposed Methodology: Feature Extraction





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

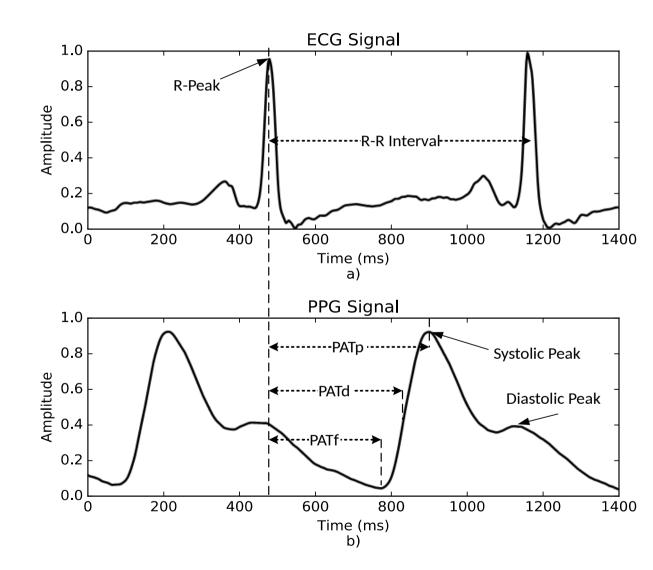
- Whole-based representation of signals
- Fully automated feature extraction and selection
- Works on almost every valid signal
- Large and complex feature vectors

Feature Extraction Methods: Parameter-Based



1) PAT features

2) Heart Rate (HR)



Feature Extraction Methods: Parameter-Based

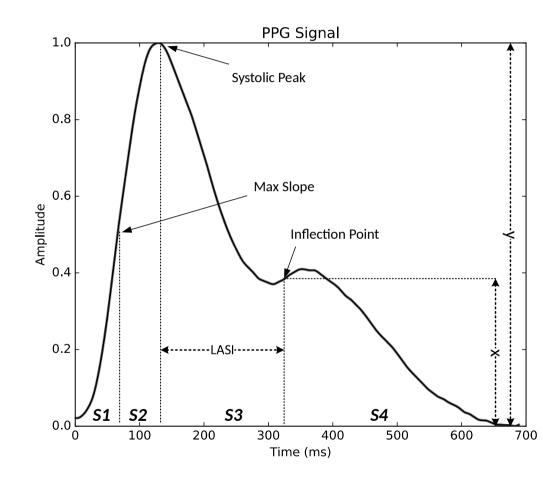


3) Augmentation Index (AI)

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

4) Large Artery Stiffness Index (LASI)

Indicator of arterial stiffness



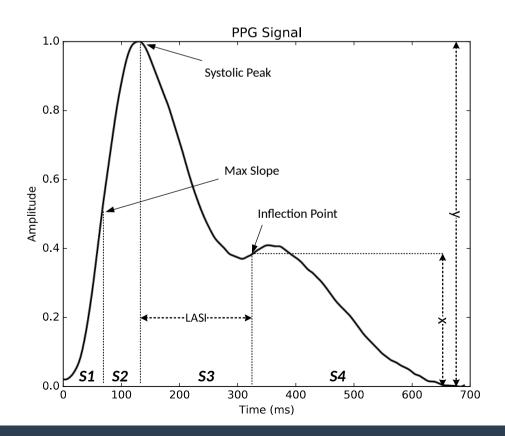
Feature Extraction Methods: Parameter-Based



5) Inflection Point Area ratio (IPA)

Ratio of heart pumping and pulse wave reflection parts

$$IPA = S4/(S1+S2+S3)$$



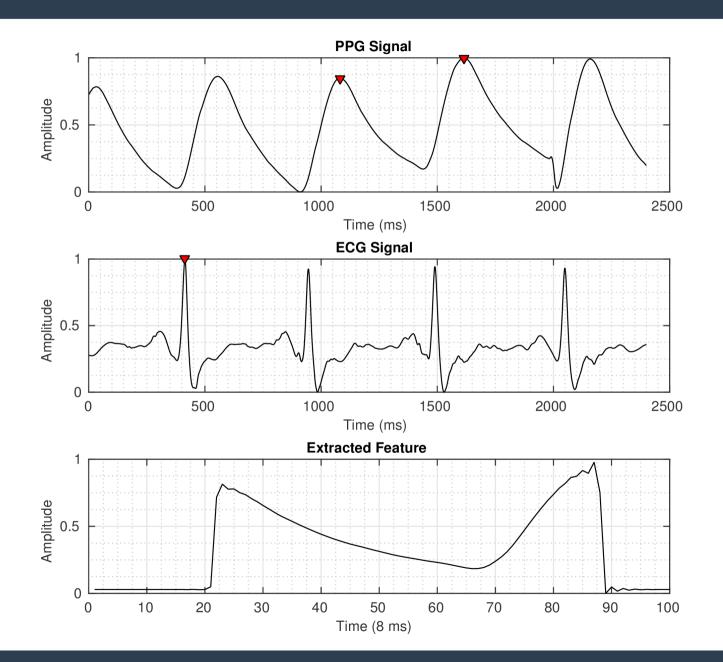
Feature Extraction Methods: Whole-Based



- 1) Selecting a processing window.
- 2) Determining R peaks and systolic peaks of the ECG and PPG signals.
- 3) Selecting the first ECG R peak as a time reference, and shifting left the PPG signal is equal to the time reference.
- 4) Selecting and cropping the PPG signal part, which is between the first and the second PPG systolic peaks.

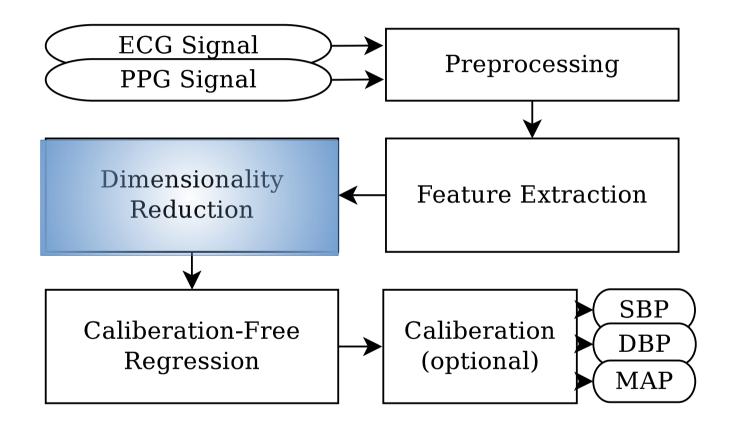
Feature Extraction Methods: Whole-Based





Proposed Methodology: Dimensionality Reduction

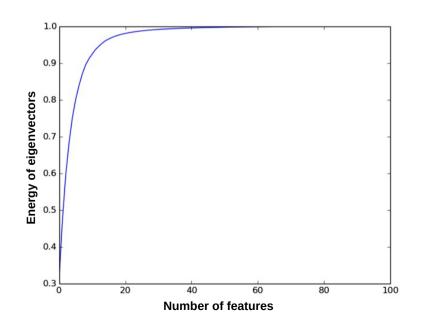




Dimensionality Reduction

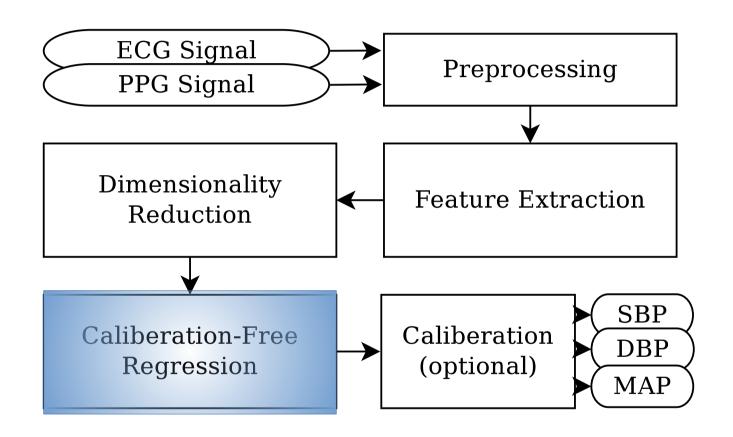


- Increasing the computational efficiency
- Reducing the number of required training data
- Using PCA on whole-based feature vectors:
 - Preserving 98% energy of eigenvectors
 - Reducing the feature length from 190 to 15



Proposed Methodology: Calibration-free Regression



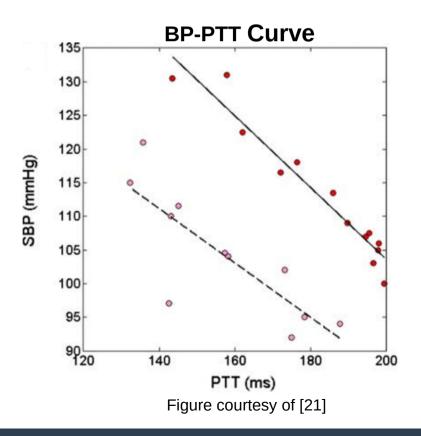


Calibration-free regression



- Here, ML is used for calibration-free BP estimation
- It is a supervised regression problem!

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



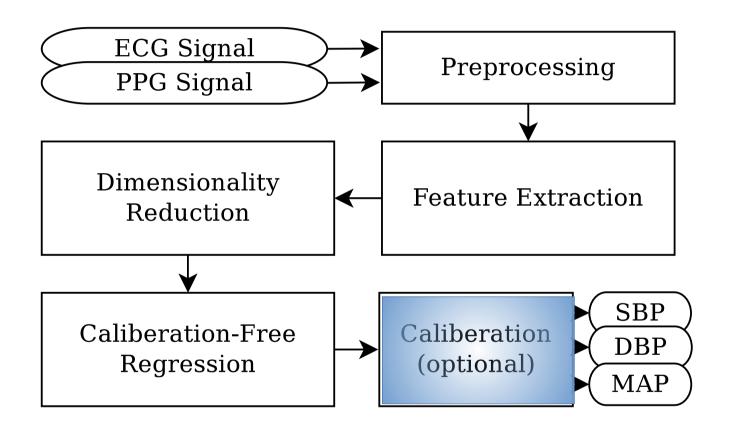
Calibration-free regression: Machine Learning



| Algorithm | Properties | Pros | Cons |
|---------------------------|--------------------------------|--|---------------------------------------|
| Linear Regression | Linear | Simple, Fast | Limited capability |
| Support Vector Machine | Sparse kernel machine | Powerful | Complex, Many hyper- parameters |
| Random Forest | Ensemble method, Bootstrap | Low bias, Fast | _ |
| Adaptive Boosting | Ensemble method with weighting | Works out-of- the-box, Focus on harder samples | Slow |

Proposed Methodology: Calibration

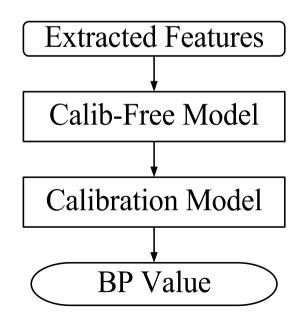




Calibration



- ✓ Optional
- ✓ One point
- ✓ Improves the results
- X Disqualifies the method from the standards



Outline: Proposed Methodology



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → Hardware Implementation
- → Conclusion

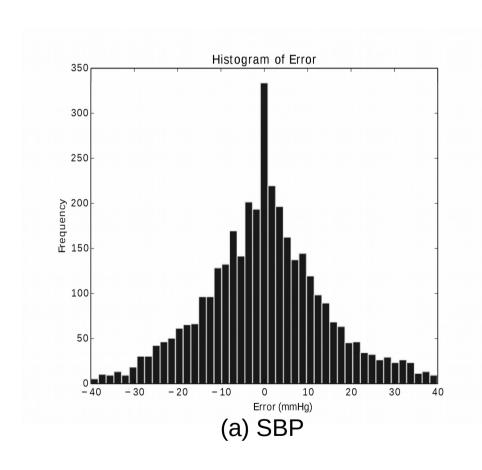


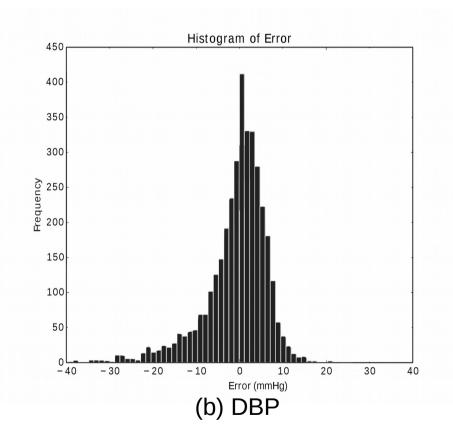
Feature extraction and regression algorithm comparison:

| | Systol | ic Blood P | ressure (1 | nmHg) | Diastolic Blood Pressure (mmHg) | | | |
|------------------------|-----------------|------------|------------|---------|---------------------------------|------------|-------------|------|
| Feature Set | Parameter-based | | Whole | e-based | Parame | eter-based | Whole-based | |
| Learner / Performance | 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 |
| 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 |



Error histogram (AdaBoost + Parameter_Based):







Comparison with other papers (AdaBoost + Parameter_Based):

| | | | DBP | | | MAP | | | SBP | |
|----------------------------|--------------|----------------------|--------|------|--------|--------|--------------|--------|--------|------|
| Work | Subjects | STD | MAE | r | STD | MAE | \mathbf{r} | STD | MAE | r |
| | (evaluation) | (mmHg) | (mmHg) | | (mmHg) | (mmHg) | | (mmHg) | (mmHg) | |
| This Work (calib-free) | 942 | 6.14 | 5.35 | 0.48 | 5.38 | 5.92 | 0.56 | 10.09 | 11.17 | 0.59 |
| This Work (calib-based) | 57 | 3.52 | 4.31 | 0.57 | - | - | - | 5.45 | 8.21 | 0.54 |
| ECG_IBP [67] (calib-based) | 22 | - | - | 0.42 | - | - | 0.46 | - | - | 0.47 |
| rPTT [68] (calib-based) | 12 | - | - | 0.14 | _ | - | 0.28 | _ | - | 0.62 |
| BPTT [69] (calib-based) | 30 | 6.00 | - | - | _ | _ | - | 7.61 | - | - |



Evaluation using the BHS (AdaBoost+Parameter_Based):

| | | Cumulative Error Percentage | | | | | |
|-------------|---------|-----------------------------|--------------|----------|---------------|---|---------------|
| | | < | $\leq 5mmHg$ | <u> </u> | $\leq 10mmHg$ | < | $\leq 15mmHg$ |
| | DBP | (| 62.7% | (| 87.1% | (| 95.7% |
| Our Results | MAP | | 54.2% | | 81.8% | | 93.1% |
| | SBP | | 34.1% | | 56.5% | | 72.7% |
| | grade A | Ţ | 60% | 7 | 85% | Ţ | 95% |
| BHS [71] | grade B | | 50% | | 75% | | 90% |
| | grade C | | 40% | | 65% | | 85% |



Evaluation using the AAMI (Random Forest+Parameter_Based):

| | | ME | STD | Subjects |
|-------------|---------------|----------|---------------|-----------|
| | | (mmHg) | (mmHg) | |
| | Diastolic | 0.36 🗸 | 5.70 ✓ | 942 🗸 |
| Our Results | Mean Pressure | 0.16 | 5.25 〈 | 942 🗸 |
| | Systolic | -0.06 ✓ | 9.88 | 942 🗸 |
| AAMI [72] | SBP and DBP | ≤ 5 | ≤ 8 | ≥ 85 |

Outline: Hardware Implementation



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → <u>Hardware Implementation</u>
- → Conclusion

Hardware Implementation

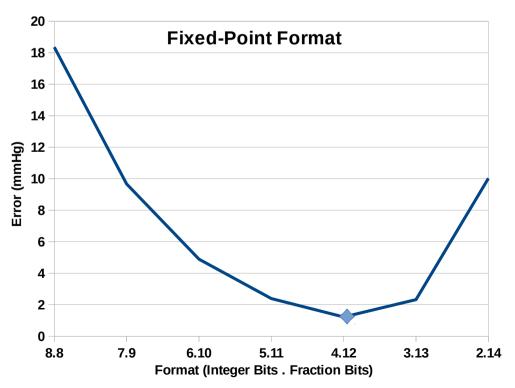


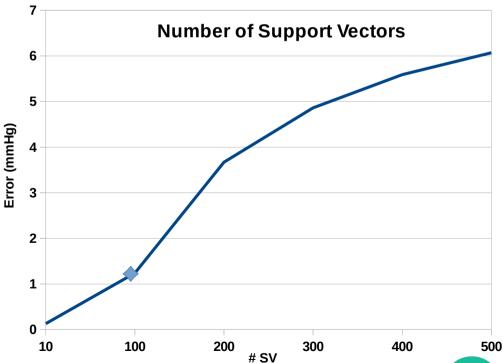
- Processing pipeline
 - Preprocessing
 - Feature extraction
 - Regression
- Regression requires hardware implementation
- SVM is selected for HW implementation as
 - Its performance in BP estimation
 - Its applications in mHealth

Python Simulation



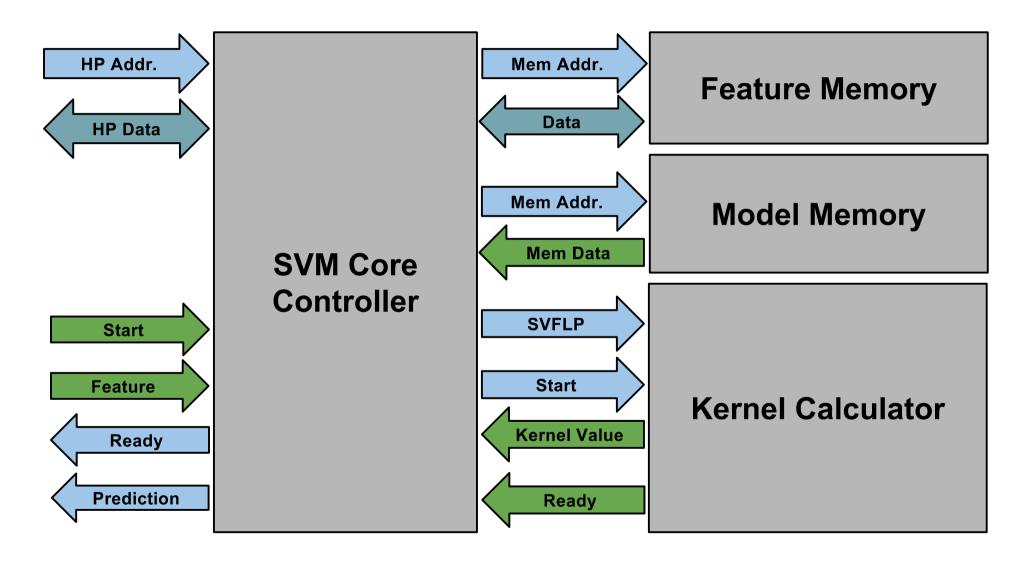
- Fixed-point analysis
- Model conversion
- Test vector generation





SVM Co-processor





SVM Co-processor: Controller



- Communicates with the host processor
- Controls the internal co-processor modules
- Consists of two 16-bit counters and a 15-state FSM

SVM Co-processor: Memory Modules



Features Memory

- Stores feature vectors
- Flexibility in input vect. length
- One port block RAM (1xRW)

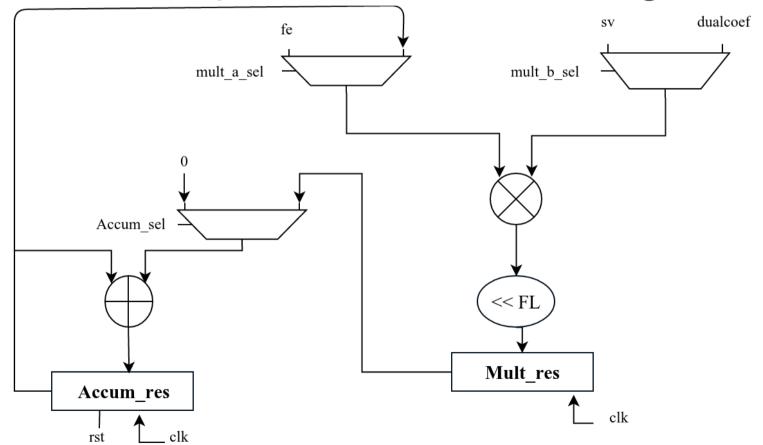
Model Memory

- Stores the SVM model
- Special memory layout
- Two port block RAM (1xR+1xW)

SVM Co-processor: Kernel Calculator



- The kernel computation core
- Consists of a 16-bit counter, an execution core, a 7-state FSM
- Efficient data manipulation and resource sharing



SVM Co-processor: Results



Resource utilization (xq7z020):

| Site Type | Used | Available | Utilization |
|-------------------------|------|-----------|-------------|
| Slice LUTs | 200 | 53200 | 0.38 |
| - LUT as Logic | 200 | 53200 | 0.38 |
| - LUT as Memory | 0 | 53200 | 0.00 |
| Slice Registers | 207 | 106400 | 0.19 |
| - Register as Flip Flop | 207 | 106400 | 0.19 |
| - Register as Latch | 0 | 106400 | 0.00 |
| Block RAM Tile | 32.5 | 140 | 23.21 |
| DSP48E1 | 1 | 220 | 0.45 |

- Timing (n_sv=200, n_fe=13, clk=100MHz):
 - total computation time = 40.305 us (~4030 clk)
 - kernel computation time = 190 ns (~19 clk)
 - state transition, initialization, etc. = 40305ns-190ns*200 = 2305 ns (~230 clk)

Outline: Conclusion



- → Blood Pressure
- → BP Measurement Methods
- → Background
- → Proposed Methodology
- → Results
- → Hardware Implementation
- → Conclusion

Conclusion



- Capability of continuous BP monitoring → cuff-less method
- Indirect calculation of BP → employing powerful regression algorithms
- Subject specific parameters → using the information from the vital signals
- Evaluation using established health standards → novel calibration-free method
- mHealth design considerations → efficient SVM core

Publications



- M. Kachuee, M. M. Kiani, H. Mohammadzade, M. Shabany, Cuff-Less Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring, IEEE Transactions on Biomedical Engineering (TBME), 2016.
- M. Kachuee, M. M. Kiani, H. Mohammadzade, M. Shabany, Cuff-Less High-Accuracy Calibration-Free Blood Pressure Estimation Using Pulse Transit Time, IEEE International Symposium on Circuits and Systems (ISCAS), 2015.

References



- W. H. Organization et al., World Health Statistic 2015. World Health Organization, 2015.
- R. Mukkamala et al., "Toward ubiquitous blood pressure monitoring via pulse transit time: Theory and practice," IEEE Trans. Biomed. Eng., vol. 62, no. 8, pp. 1879–1901, Aug 2015.
- M. Y. Wong et al., "An evaluation of the cuffless blood pressure estimation based on pulse transit time technique: a half year study on normotensive subjects," Cardiovascular Engineering, vol. 9, no. 1, pp. 32–38, 2009.
- M. Elgendi, "On the analysis of fingertip photoplethysmogram signals," CCR, vol. 8, no. 1, pp. 14–25, 2012. "IEEE standard for wearable cuffless blood pressure measuring devices," IEEE Std 1708-2014, pp. 1–38, Aug 2014.
- D. Donoho, "De-noising by soft-thresholding," IEEE Trans. Inform Theory, vol. 41, no. 3, pp. 613–627, 1995.
- D. B. McCombie et al., "Adaptive blood pressure estimation from wearable PPG sensors using peripheral artery pulse wave velocity measurements and multi-channel blind identification of local arterial dynamics," in Annu. Int. Conf. Eng. Med. Bio. (EMBS). IEEE, 2006, pp. 3521–3524.



Thanks