Learning Your Heart Actions From Pulse: ECG Waveform Reconstruction From PPG

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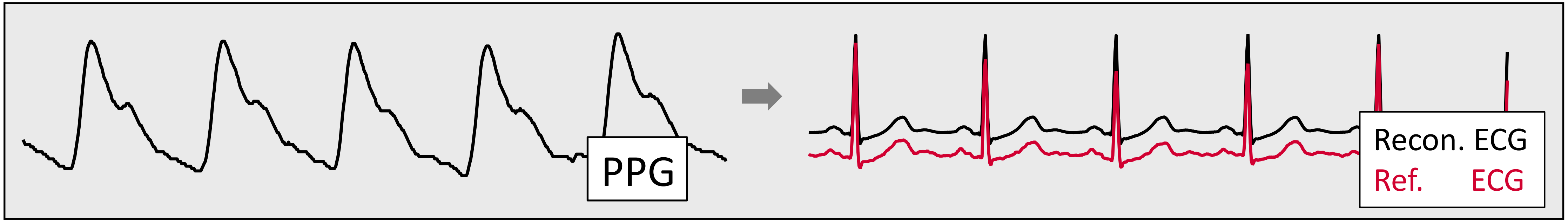
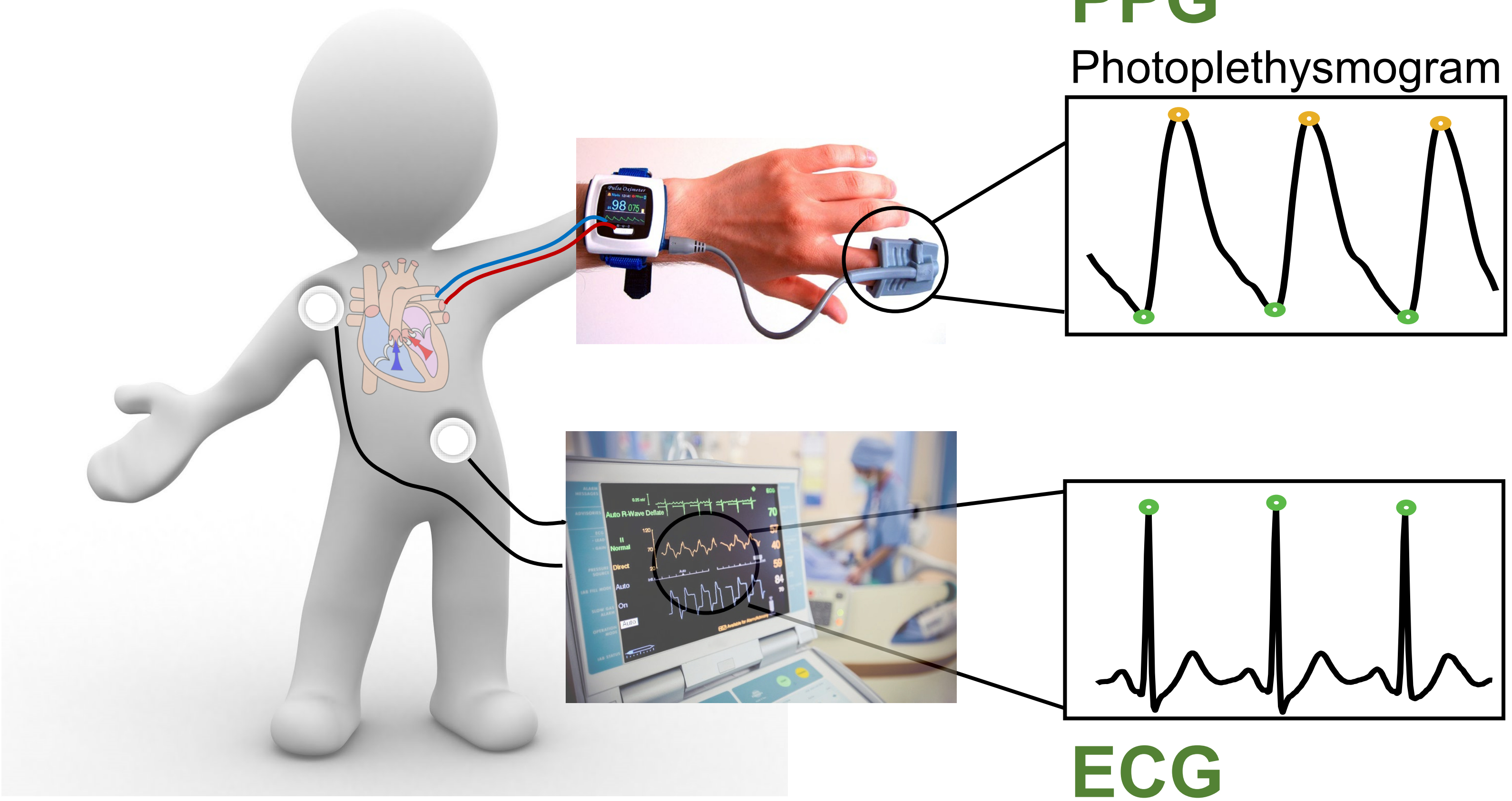


Continuous Cardiovascular Monitoring: *ECG* vs. *PPG* — Pros and Cons

PPG

Photoplethysmogram



Optical sensing

Less direct cardiac information

More user-friendly and cheaper

ECG

Electrocardiogram

Bio-electrical signal

Clinical gold standard

Restrictive; uncomfortable

ECG from PPG — Benefits and Research Problems

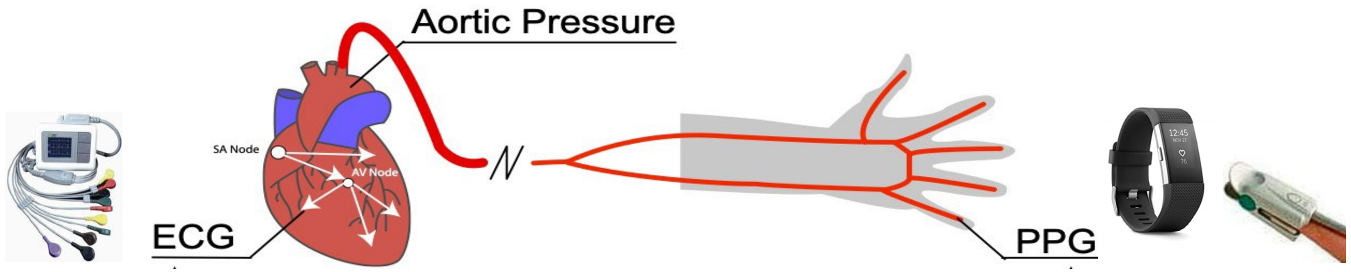
Knowledge Base | Low Cost | Continuous Real-time | User Friendly | Digital Twins Monitoring

Two major research problems:

Fundamental & our focus

1. Infer ECG from *clean* PPG?
2. Clean up noisy PPG due to movement etc.?
   - Leverage multiple sensors (e.g., accelerometers)

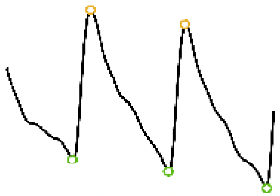
A Signal Model between ECG and PPG



Cardiac Electrical Activity → Ventricular contraction → Aortic Pressure → Blood Vessel Network → Peripheral Pulse Wave

ECG

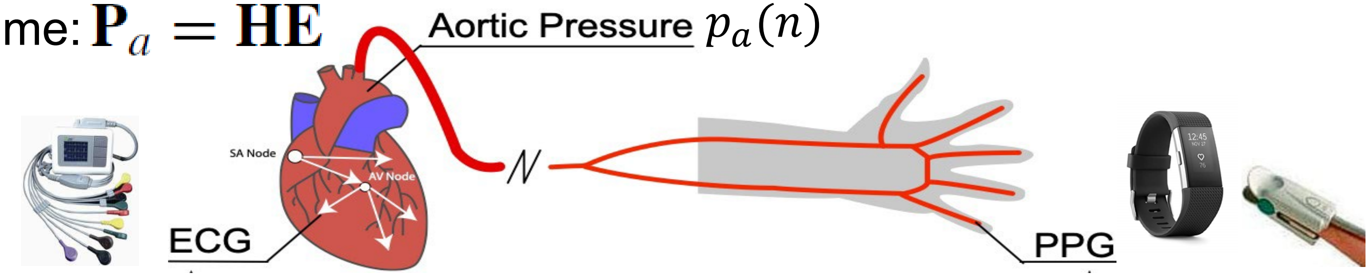
PPG



Cardiac Electrical Activity → Equiv. Filter (lowpass) → Peripheral Pulse Wave

Characterize the Signal Model Between ECG and PPG

Assume: $\mathbf{P}_a = \mathbf{HE}$



ECG: $c_y(n) = \alpha e(n) + v_y(n)$

-- $e(n)$: Myocardial activities
-- α: Human body resistance of the electrical path from the heart to the skin surface;
-- $v_y(n)$: ECG sensor noise.

$$p_p(n) = b(n) \circledast p_a(n) + v_b(n)$$

$$\mathbf{P}_p = \mathbf{B}\mathbf{P}_a + \mathbf{V}_b$$

-- $b(n)$: blood vessel as LTI channel;
-- $\circledast$: symmetric convolution operator;
--$p_p(n)$: peripheral pulse wave;
-- $v_b(n)$: model noise;
-- $\mathbf{P}_p, \mathbf{B}, \mathbf{P}_a, \mathbf{V}_b$**:** corresp. DCT coeff.

PPG: $c_x(n) = I_1 p_p(n) + I_0 + v_x(n)$

where $I_1 = I\tau_1$ and $I_0 = I\tau_0$

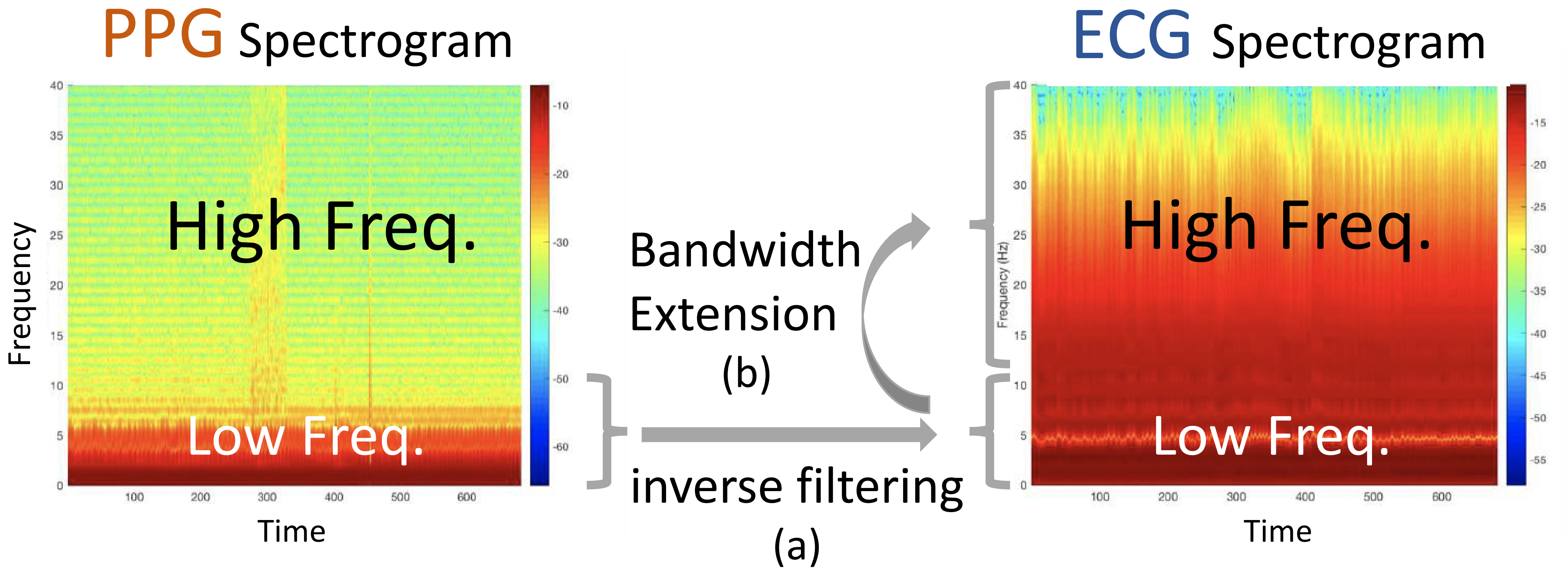
-- I: intensity of the light source
-- τ_0, τ_1: transmissive strength and reflective strength of the skin tissue.

Linear model in DCT domain

$$\boxed{\mathbf{C}_y = \mathbf{F}\mathbf{C}_x + \mathbf{C}_0 + \mathbf{V}}$$

where
$$\mathbf{F} \triangleq \alpha I_1^{-1}\mathbf{H}^{-1}\mathbf{B}^{-1}$$
$$\mathbf{C}_0 \triangleq -\alpha I_1^{-1}\mathbf{H}^{-1}\mathbf{B}^{-1}\mathbf{I}_0$$
$$\mathbf{V} \triangleq \mathbf{V}_y - \alpha\mathbf{H}^{-1}\mathbf{B}^{-1}(I_1^{-1}\mathbf{V}_x + \mathbf{V}_b)$$

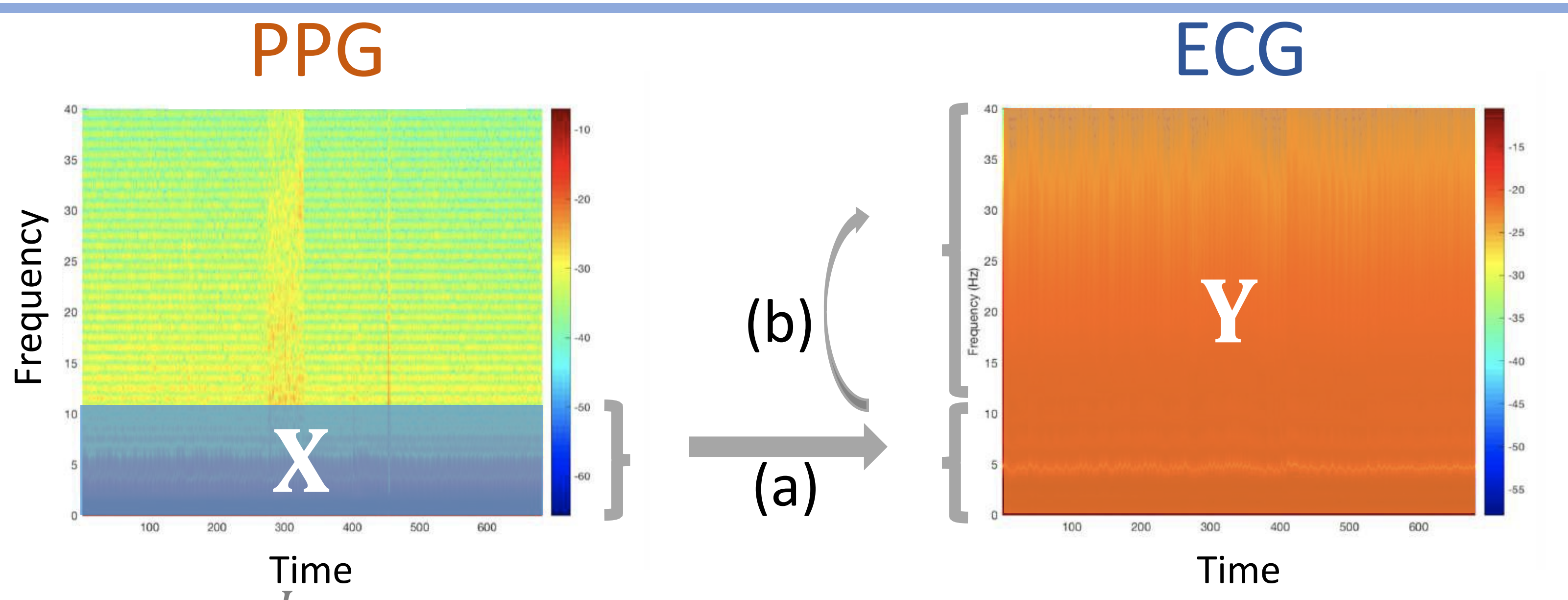
PPG to ECG: Methodology At-a-Glance



Combine (a) and (b) with *model + data supported learning*

PPG to ECG: Methodology At-a-Glance (cont.)

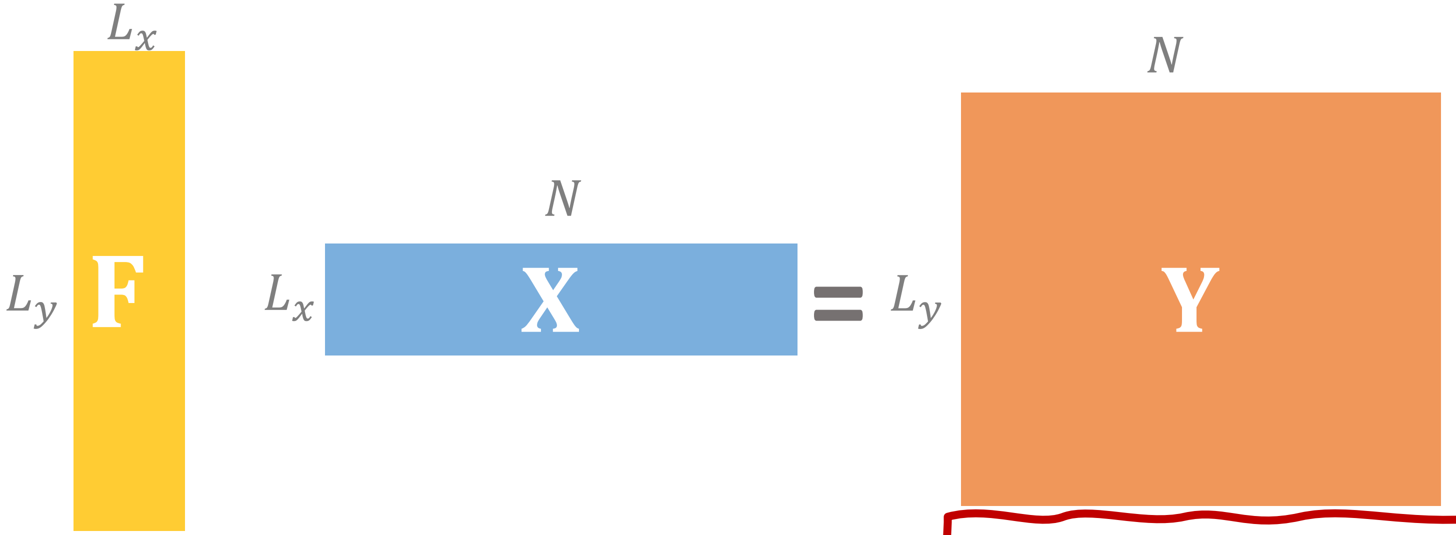
Combine (a) and (b) with model and data learning



Model in freq. domain

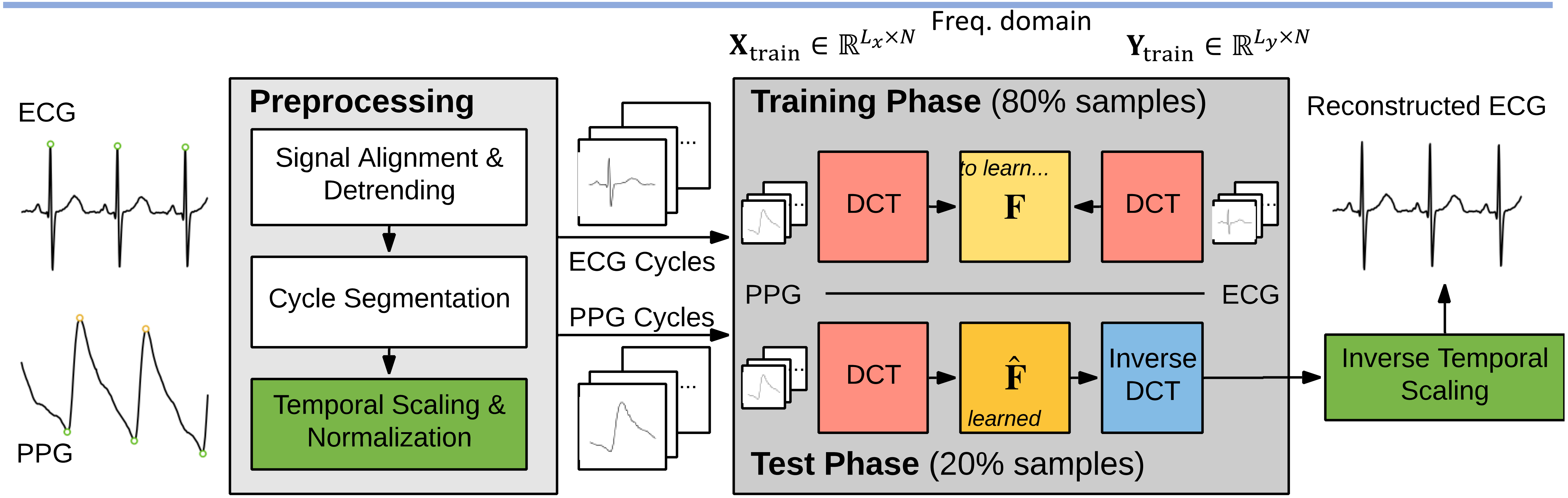
Linear transform $\mathbf{F}$:

- L_x: # PPG freq. Coeffi.
- L_y: # ECG freq. Coeffi.
- N: # time indices



Recall: Linear model in DCT domain $\boxed{\mathbf{C}_y = \mathbf{F}\mathbf{C}_x + \mathbf{C}_0 + \mathbf{V}}$

A Cycle-based Learning Framework

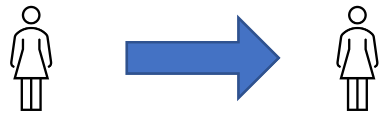


$$\hat{\mathbf{F}} = \underset{\mathbf{F}}{\operatorname{argmin}} \|\mathbf{F}\mathbf{X}_{\text{train}} - \mathbf{Y}_{\text{train}}\|_F^2 + \gamma \|\mathbf{F}\|_F^2$$

A linear transform $\hat{\mathbf{F}}$ learned by *ridge regression*

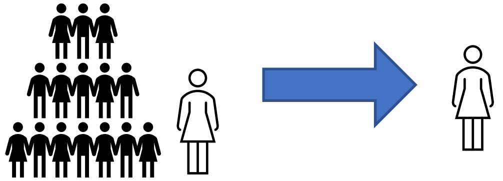
Subject Specific Model (SM) vs. Group Model (GM)

Two training setups:



1. Subject-Specific Model (SM)

Can the proposed learning system, trained by an individual's signal pairs of ECG and PPG, predict his/her ECG waveforms from unseen PPG measurements?



2. Group Model (GM)

Can a single model, trained by a group of subjects with certain trait combinations (e.g., age and weight), predict ECG waveforms from unseen PPG measurements for an individual in the training group?

Recall: Linear model in DCT domain $\boxed{\mathbf{C}_y = \mathbf{F}\mathbf{C}_x + \mathbf{C}_0 + \mathbf{V}}$

where
$$\mathbf{F} \triangleq \alpha I_1^{-1}\mathbf{H}^{-1}\mathbf{B}^{-1}$$
$$\mathbf{C}_0 \triangleq -\alpha I_1^{-1}\mathbf{H}^{-1}\mathbf{B}^{-1}\mathbf{I}_0$$
$$\mathbf{V} \triangleq \mathbf{V}_y - \alpha\mathbf{H}^{-1}\mathbf{B}^{-1}(I_1^{-1}\mathbf{V}_x + \mathbf{V}_b)$$

Datasets for System Evaluation: Diverse Combinations of Age, Weight, and Health Conditions

Capnobase TBME-RR (by UBC, publicly available) [1]

- Collected during elective surgery and routine anesthesia.
- 29 Children and 13 adults (age: min: 1, max: 63, and median: 14; weight: min: 9 kg, max: 145 kg, and median: 49 kg)).

Self-Collected UMD Dataset:

- Self-collected data using consumer-grade PPG and ECG sensors.
- Two UMD students participated in this over-two-week data collection.

Mini-MIMIC (selected data from MIT MIMIC III database [2])

- ICU data with various cardio patients and non-cardio ones.
- 103 patients in total. Each patient has three sessions of 5-min ECG and PPG recordings collected within several hours.

[1]. Karlen, W., Raman, S., Ansermino, J. M., & Dumont, G. A. (2013). Multiparameter Respiratory Rate Estimation from the Photoplethysmogram. IEEE Transactions on Biomedical Engineering, 60(7), 1946-1953.

[2]. Johnson, A. E., Pollard, T. J., Shen, L., Li-wei, H. L., Feng, M., Ghassemi, M., ... & Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. Scientific data, 3, 160035.

Evaluation Methods

Two Evaluation Metrics:

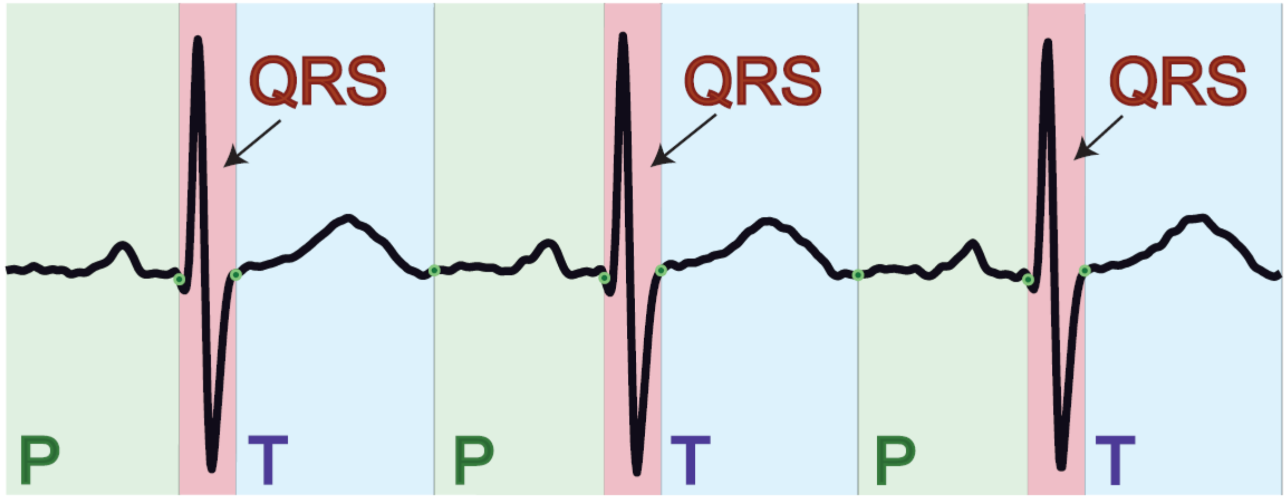
- Relative Root Mean Square Error

$$\mathrm{rRMSE} = \frac{\|\boldsymbol{y} - \widehat{\boldsymbol{y}}\|_2}{\|\boldsymbol{y}\|_2}$$

- Pearson's Correlation Coefficient

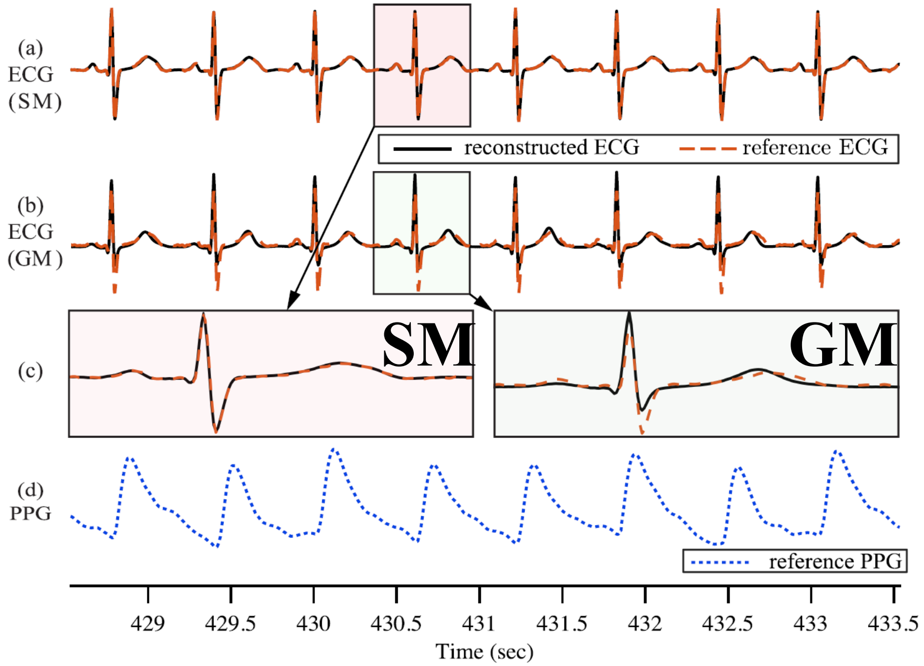
$$\rho = \frac{(\boldsymbol{y} - \bar{y})^{\mathrm{T}}(\widehat{\boldsymbol{y}} - \bar{\hat{y}})}{\|\boldsymbol{y} - \bar{y}\|_2 \left\|\widehat{\boldsymbol{y}} - \bar{\hat{y}}\right\|_2}$$

Segments Evaluation:



Evaluation on Dataset 1: TBME-RR dataset

- One example: 4 years old, 18 kg
- Pearson's correlation coeff.
  SM: 0.99
  GM: 0.88

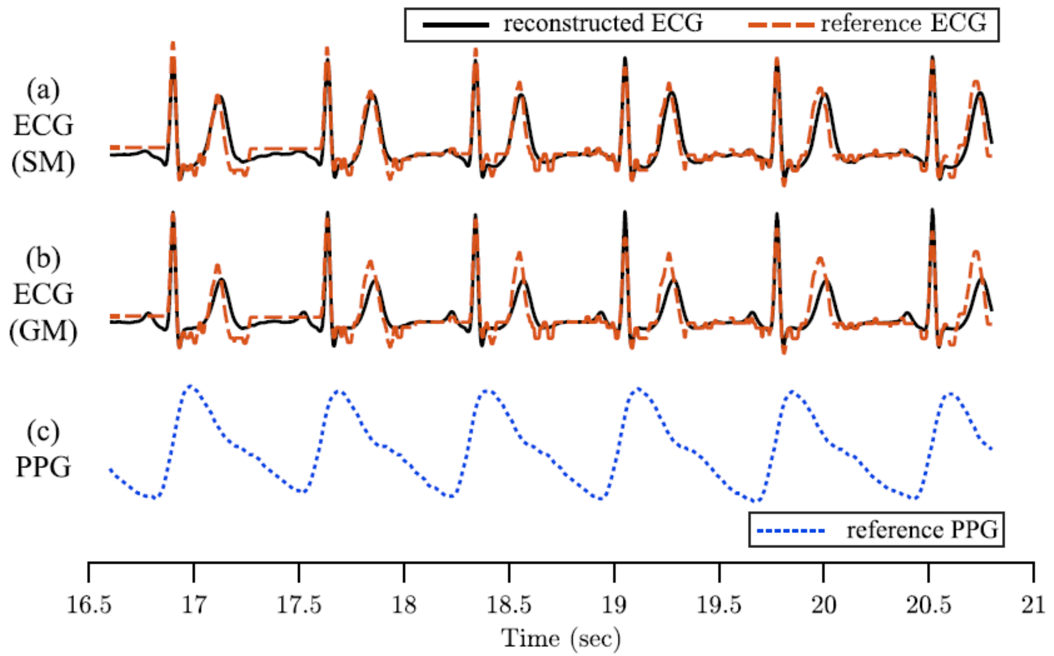


- Overall performance

	Subject Specific Model (SM)				Group Model (GM)			
Average	P	QRS	T	all	P	QRS	T	all
rRMSE	0.27	0.13	0.28	0.17	0.52	0.36	0.72	0.42
ρ	0.87	0.99	0.92	**0.98**	0.69	0.94	0.71	**0.91**

Evaluation on Dataset 2: UMD dataset

- One example:
  - Pearson's correlation coeff.
    SM: 0.92
    GM: 0.87



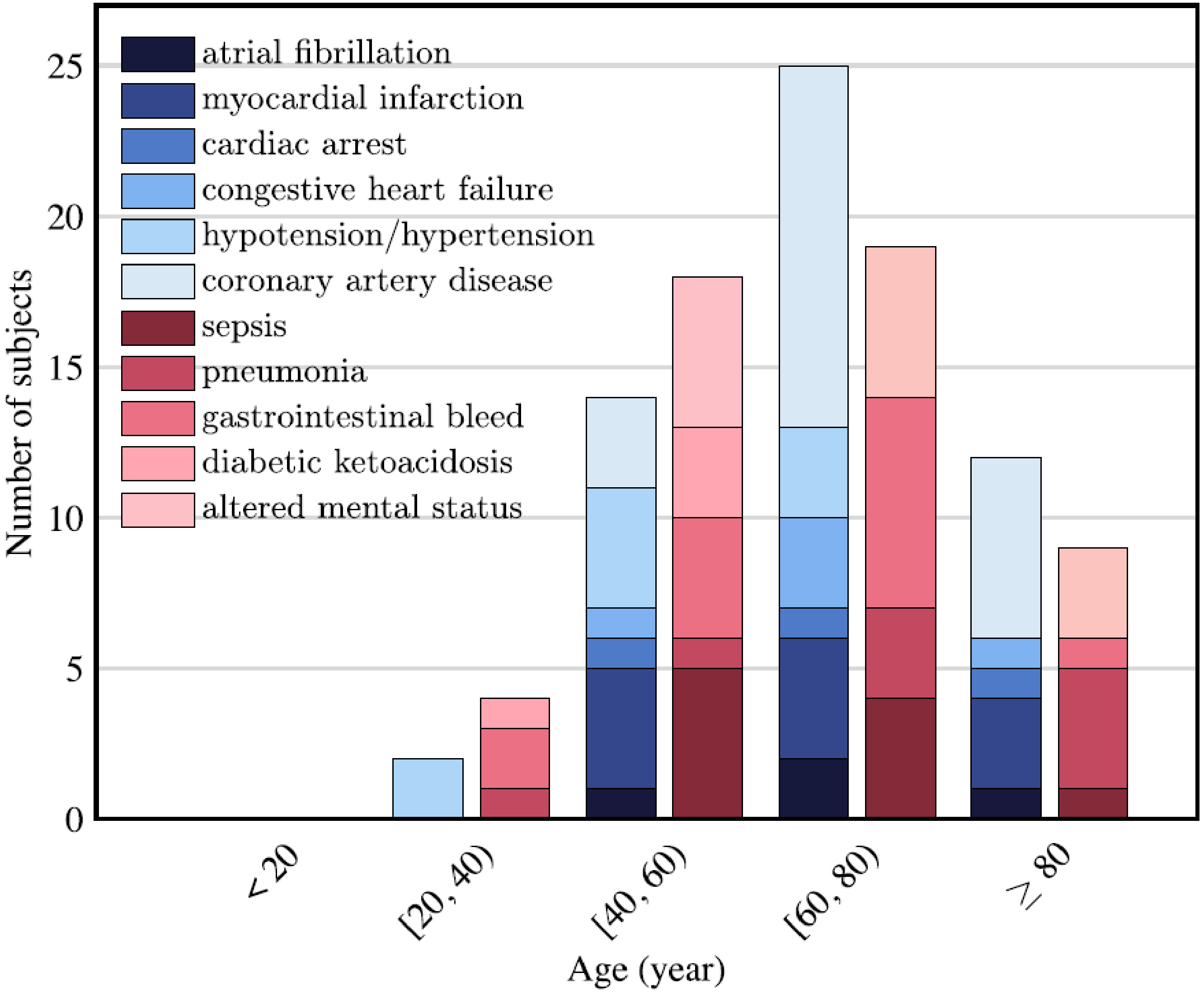
- Overall performance

	Subject Specific Model (SM)				Group Model (GM)			
Average	P	QRS	T	all	P	QRS	T	all
rRMSE	0.66	0.28	0.57	0.43	0.72	0.30	0.59	0.45
ρ	0.58	0.97	0.84	**0.90**	0.50	0.96	0.83	**0.89**

Dataset 3: Mini-MIMIC III

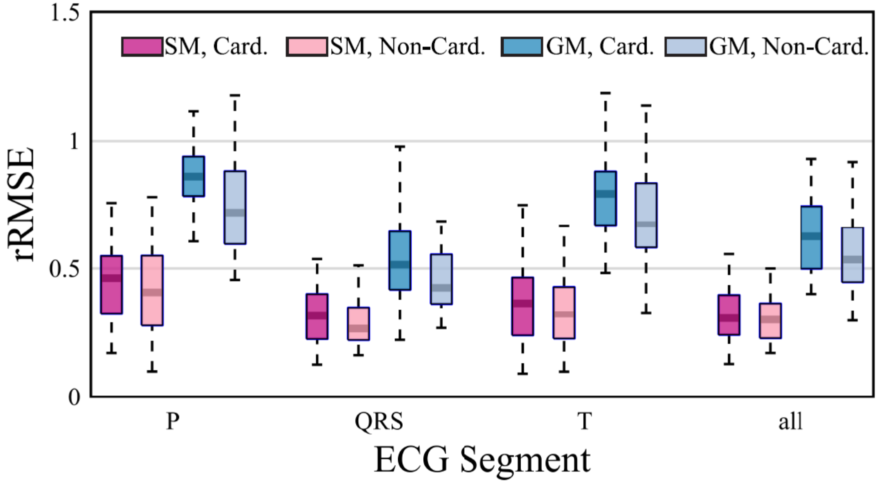
Selected PPG and ECG data from MIMIC III database [2]

- 50 Cardiac Patients
- 53 Non-cardiac Patients

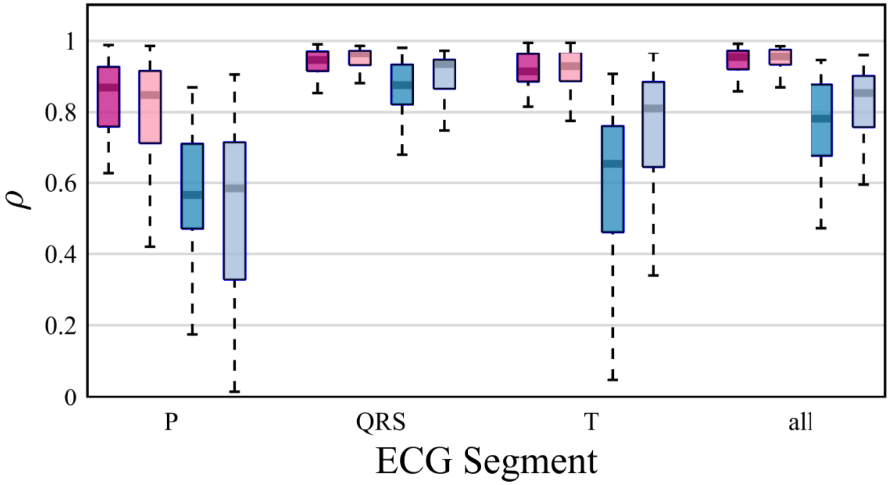


Evaluation on Dataset 3: Mini-MIMIC III

Overall performance:

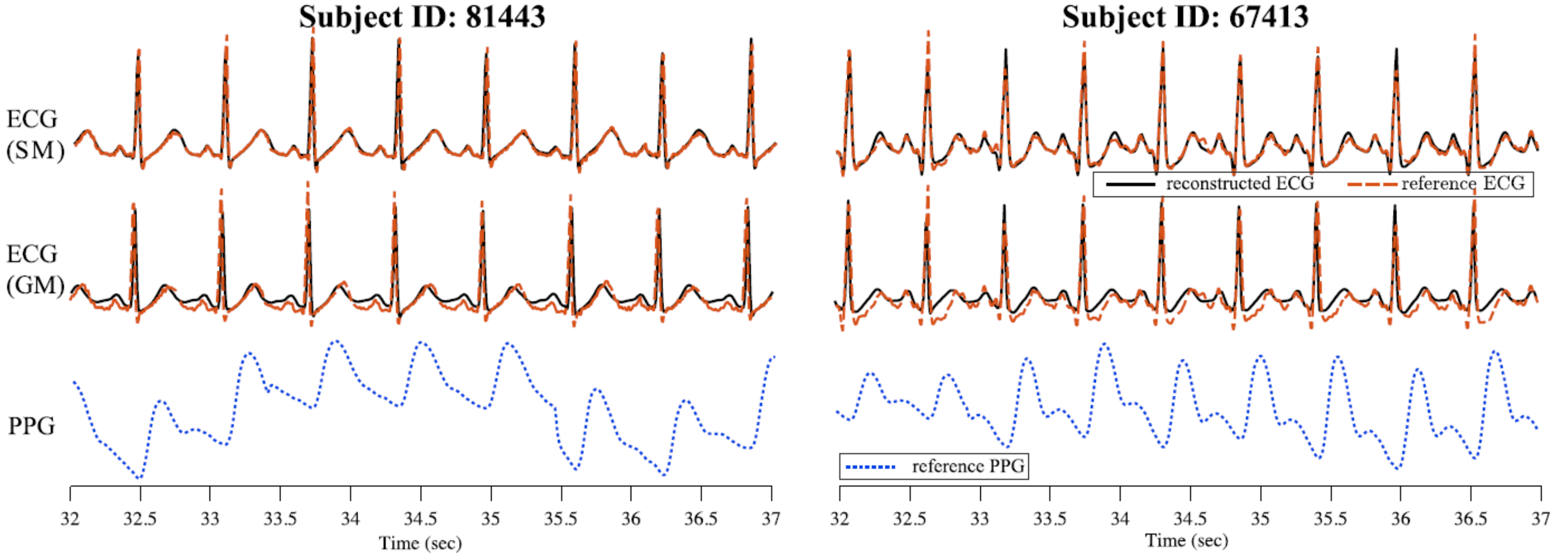


(a)



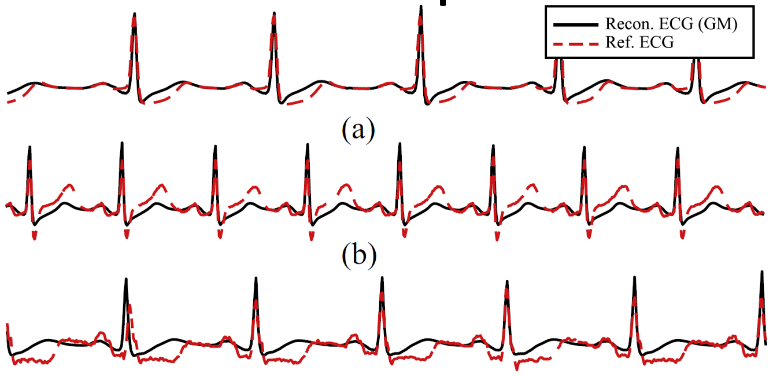
(b)

Good examples:



(a) (b)

"low performance" examples:



(a)

(b)

(c)

Cardio Disease Classification (subset from Mini-MIMIC III)

Confusion matrices & classification accuracy of SVM (w/ polynomial kernel) on …

	Ori. ECG (ref.)	**Recon. ECG (Proposed)**	**Ori. PPG**
Accuracy:	99.6%	**99.3%**	76.6%

Confusion matrix from number of PCs = 100

Ori. ECG (ref.)

True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	100.0%	0.0%	0.0%	0.0%	0.0%
STMI	0.0%	100.0%	0.0%	0.0%	0.0%
NSTMI	0.0%	0.0%	100.0%	0.0%	0.0%
HYPO	0.0%	1.8%	0.0%	98.2%	0.0%
CAD	0.0%	0.0%	0.0%	0.0%	100.0%

Recon. ECG (Proposed)

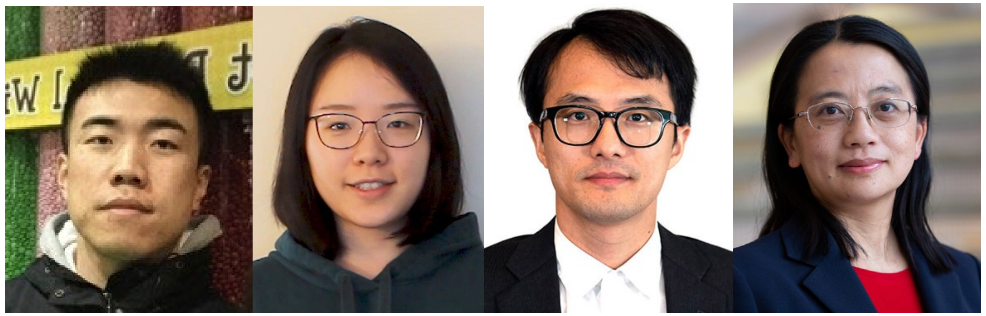
True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	100.0%	0.0%	0.0%	0.0%	0.0%
STMI	0.0%	100.0%	0.0%	0.0%	0.0%
NSTMI	4.3%	0.0%	95.7%	0.0%	0.0%
HYPO	0.0%	0.0%	0.0%	100.0%	0.0%
CAD	0.0%	0.0%	0.0%	0.0%	100.0%

Ori. PPG

True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	81.5%	4.6%	9.2%	1.5%	3.1%
STMI	8.5%	83.1%	5.1%	3.4%	0.0%
NSTMI	22.5%	17.5%	55.0%	2.5%	2.5%
HYPO	1.8%	3.5%	1.8%	93.0%	0.0%
CAD	6.5%	22.6%	19.4%	0.0%	51.6%

Conclusion

- Proposed and justified a physiological model to mathematically characterize the relationship between the ECG and PPG time-series signals using electrical, biomechanical, and optophysiological principles;
- Developed a principled learning framework based on the proposed physiological model and achieved encouraging accuracy of ECG reconstruction;
- Suggested an encouraging potential for a more user-friendly, low-cost, continuous, and long-term cardiac monitoring that supports and promotes public health, especially for people with special needs;
- Open a new direction to leverage a rich body of clinical ECG knowledge and transfer the understanding to enrich the knowledge base for PPG or other data from wearable devices.



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