RespNet: A deep learning model for extraction of respiration from photoplethysmogram

Keerthi Ram

Healthcare Technology Innovation Centre, IIT Madras
June 28, 2019

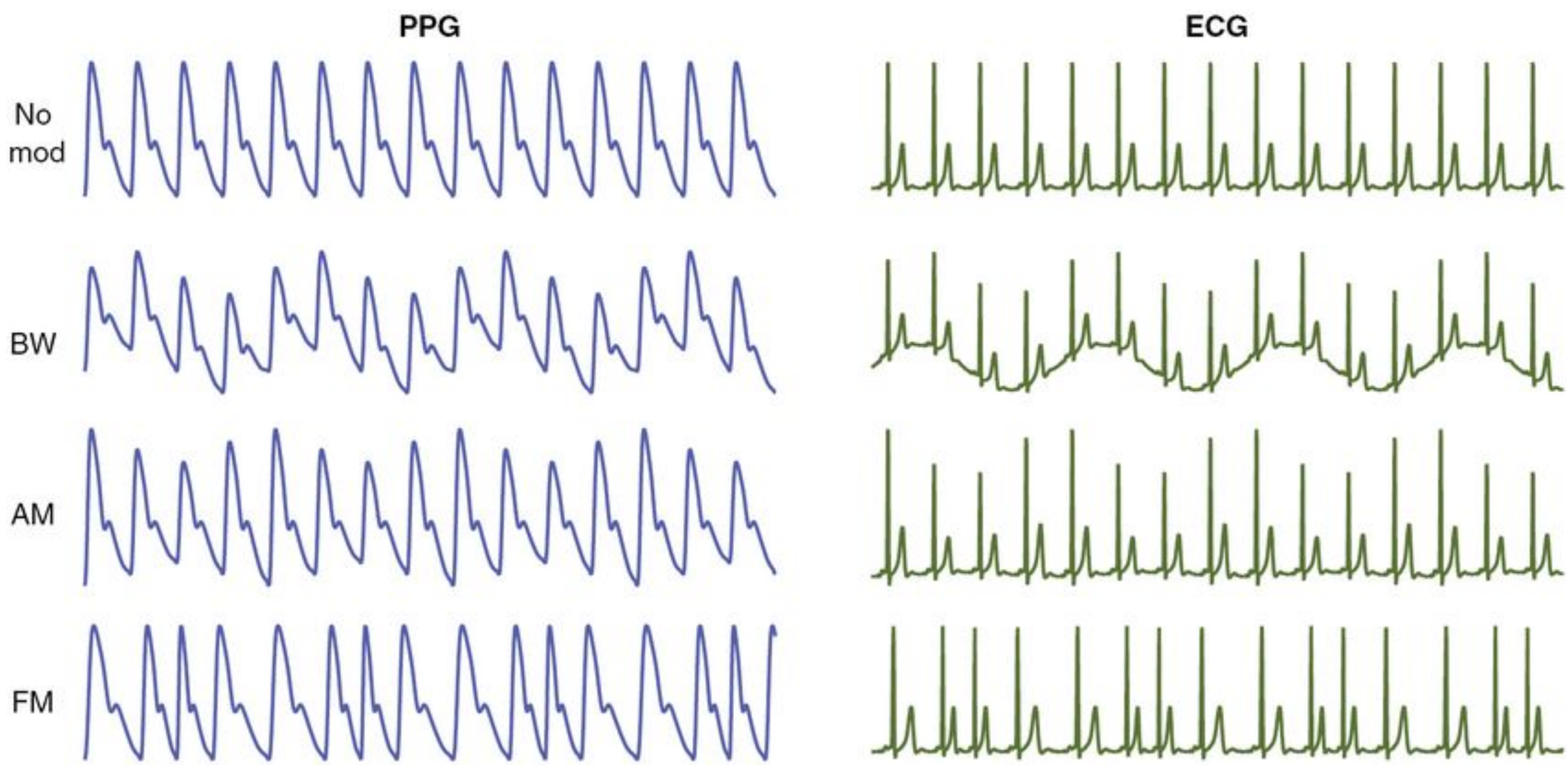
0. Overview

- Introduction to Respiration extraction from PPG
- Extraction of respiratory signal from PPG
- Dataset Description
- Proposed Network
  - Architecture
  - Training method
  - Evaluation method
- Experiments & Results
- Conclusion

1. Introduction to Respiration Extraction from PPG

- **Modalities of Indirect measurement of respiration**
  - Electrocardiogram (ECG)
  - Photoplethysmogram (PPG)
- **Effects of respiration on ECG and PPG**
  - Baseline wander
  - Amplitude modulation
  - Frequency modulation
- **Changes caused by respiratory movements reflected in PPG**
  - Change in stroke and blood volume
  - Respiratory sinus arrhythmia
    - Characterized by increase in heart rate during inhalation and decrease in heart rate during exhalation
- **Modality for estimation of respiratory ailments**
  - Proliferation of consumer-grade wearables with PPG sensing can allow for unobtrusive monitoring of respiration

2. Introduction to Respiration Extraction from PPG



Different types of respiration associated modulations of PPG,ECG [1]

3. Extraction of respiratory signal from PPG

- **Primary focus** of literatures in the domain of extraction of respiratory signal from PPG [1][2]
  - Estimation of respiration rate from PPG
- **Best performing methods** for estimating respiration rate from PPG
  - Baseline Wander (BW)
  - Amplitude Modulation (AM)
  - Frequency Modulation (FM) of extracted respiratory signals
- Extracting **Respiratory pattern from PPG**
  - more comprehensive evaluation of sleep conditions and other chronic respiratory ailments
- **Prinable et al. [3]** propose a feature based method to estimate tidal volume from input PPG signal.

4. Dataset Description - Vortal dataset

- The Vortal dataset is comprised of ECG and reflectance PPG along with reference respiratory signals
- **Reference respiratory signals**
  - Impedance Pneumography
  - Oral-Nasal pressure signals
- **Characteristics of sample population**
  - Wide range of respiratory rate from young subjects through a post exercise recording session
  - Healthy volunteers of different age groups at supine posture
- **Sampling Rate**
  - ECG -500 Hz
  - PPG -500 Hz
  - Reference respiratory signals- 25Hz
- **Model input**
  - PPG and capnometry signals were resampled to 256Hz
  - Window size- 8 seconds interval
  - Train set - 80% ; Test set- 20%

5. Dataset Description - CapnoBase

- The CapnoBase dataset consists of 8 minute recordings of ECG and transmittance PPG along with capnometry
- **No of subjects** - 42
- **Sample population**: Undergoing elective surgery or routine anesthesia
- **Sampling rate**
  - ECG 300 Hz
  - PPG-100Hz (resampled to 300Hz)
  - Capnometry- 25Hz (resampled to 300Hz)
- **Model input**
  - PPG and capnometry signals were resampled to 256Hz
  - Window of 8 seconds interval was considered
  - No of subjects for train set - 34/42
  - No of subjects for test set - 8/42

6. Proposed Network

- **Architecture Used:**
  - UNet (IncResUNet)

- **Problem Formulation:**
  - Similar to image segmentation, we train the network to apply filters to extract respiration from PPG (i.e):

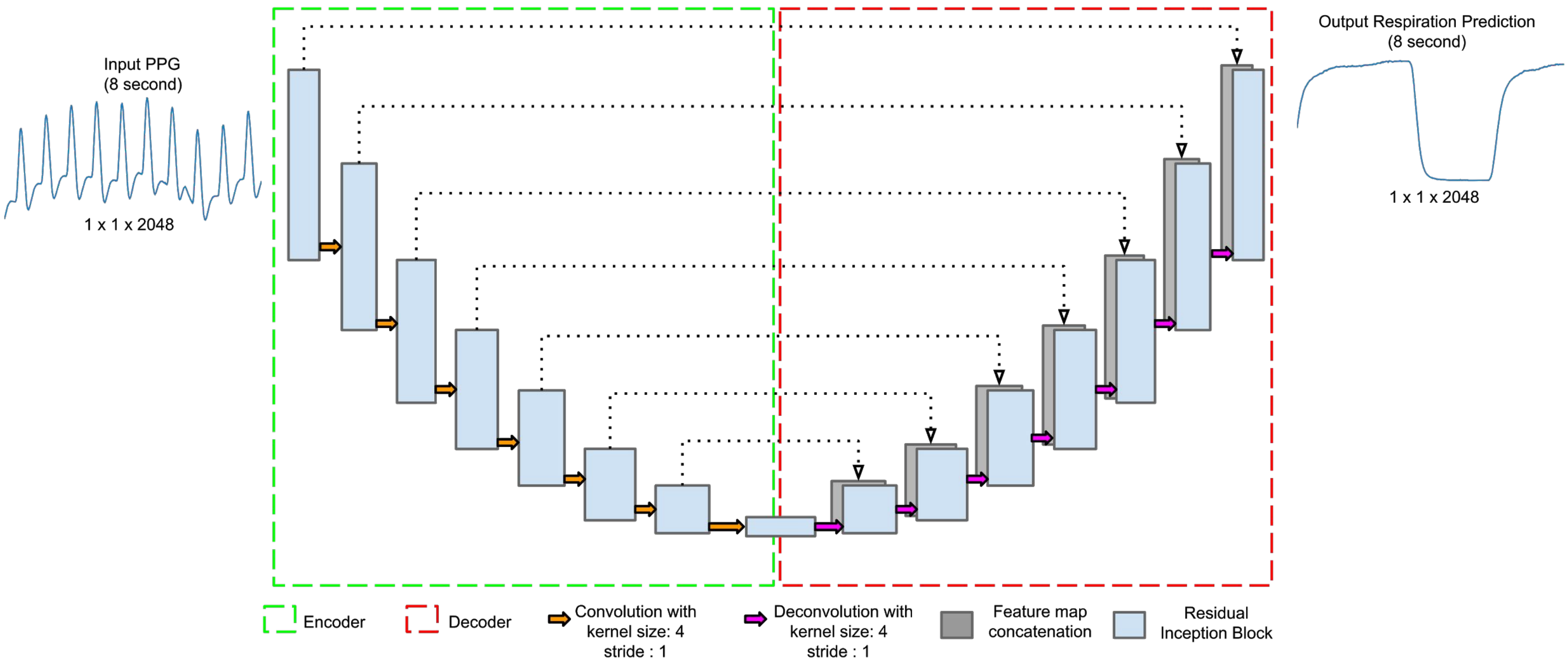
    We train a network consisting on encoder and decoder F_1 , F_2 to take input $x^{(i)}$ and output $y^{(i)}_{pred}$ using convolutional filters.

$$z_1^{(i)} = F_1(x^{(i)}; \theta_1)$$

$$y_{pred}^{(i)} = F_2(z_1^{(i)}; \theta_2)$$

Where z_1 is the output of encoder and θ_1 and θ_2 are weights of encoder and decoder respectively

7. Proposed Network - Architecture



Architecture of the proposed network

8. Proposed Network - Training Method

- Uses IncResU-Net network which is used in 2D medical image segmentation application [4]

- **Training Settings:**
  - Loss: Smooth L1 Loss
  - Optimizer: Stochastic Gradient Descent
  - Epochs: 2000
  - Batch Size: 256
  - Learning Rate: 0.01
  - Momentum: 0.7
  - Implemented in PyTorch

9. Proposed Network - Evaluation Method

- **Evaluation Metrics:**
  - Cross Correlation and Lag
  - Mean Square Error (MSE)

- Evaluation carried out for both datasets using corresponding ground truth respiratory signals in test set.

- **Comparison Metrics obtained from RRest toolbox [5] :**
  - Amplitude Modulation (WAM)
  - Frequency Modulation (WFM)

- All signals rescaled to 60 Hz before evaluation for compatibility with RRest predictions

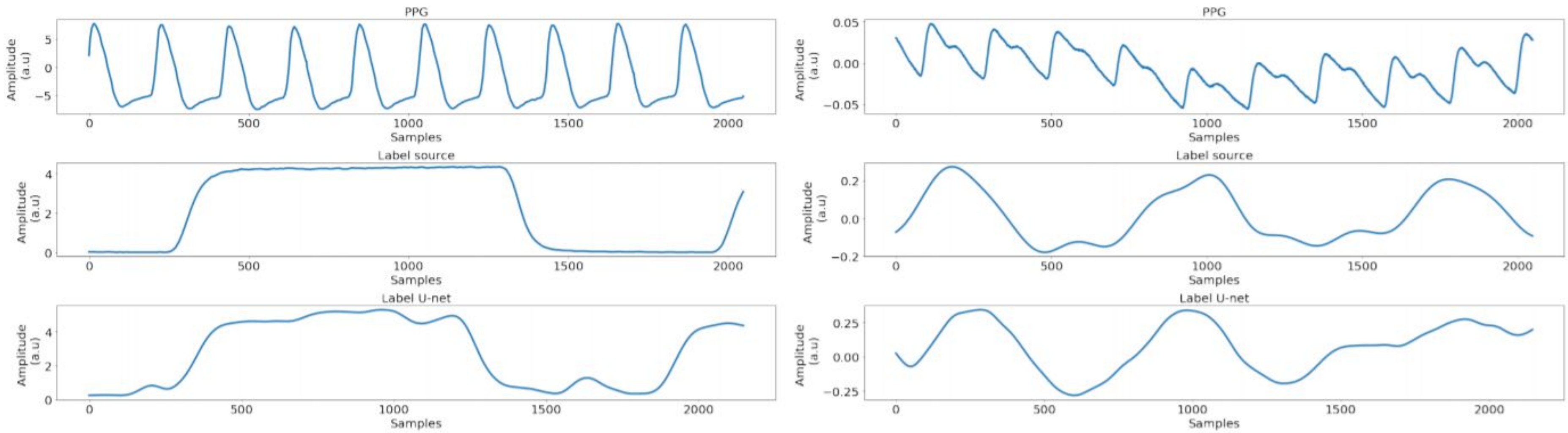
- Min Max scaling performed to all signals before comparison

10. Experiments and Results

Dataset	Method	MSE	Cross-Correlation	Lag
CapnoBase	WAM	0.301	0.925	0.024
	WFM	0.364	0.858	0.014
	RespNet (Ours)	**0.262**	**0.933**	**0.004**
Vortal	WAM	0.247	0.927	1.929
	WFM	0.272	0.853	1.706
	RespNet (Ours)	**0.145**	**0.931**	**0.052**

TABLE I: Comparison between RespNet and other methods

11. Experiments and Results



(a) (b)

(a) Sample PPG, reference respiration signal (label source) & RespNet prediction (label U-net) for CapnoBase dataset

(b) Sample PPG, reference respiration signal and RespNet prediction for Vortal dataset

12. Conclusion

- **Summary:**
  - The present work describes a novel approach to extract the respiration signal from PPG as opposed to only performing respiratory rate estimation
  - Proposed network utilizes PPG signal as input and allows training with any corresponding reference respiratory signal
  - Superior performance compared to traditional methods:
    - MSE: 0.263, 0.145
    - Cross Correlation: 0.933, 0.931
  - Indicates feasibility of extracting respiratory signal from PPG using fully convolutional networks.
  - Can be used in applications like sleep monitoring and inexpensive breathing retraining sensors

13. Conclusion

- **Future Scope:**
  - Extensive training on a wide range of breathing anomalies
  - Extending usage to wrist worn reflectance PPG
  - Performance study of network under mild and major motion conditions
  - Long term performance study

References

1. Charlton P.H. and Bonnici T.B. et al. An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram, Physiological Measurement, 37(4), pp. 610-26, 2016. DOI: 10.1088/0967-3334/37/4/610

2. Dehkordi, Parastoo, et al. "Extracting instantaneous respiratory rate from multiple photoplethysmogram respiratory-induced variations." Frontiers in physiology 9 (2018).

3. J. B. Prinable, P. W. Jones, C. Thamrin, and A. Mcewan, "Using a recurrent neural network to derive tidal volume from a photoplethysmograph," 2018.

4. S. M. Shankaranarayana, K. Ram, K. Mitra, and M. Sivaprakasam, "Fully convolutional networks for monocular retinal depth estimation and optic disc-cup segmentation," arXiv preprint arXiv:1606.04797, February 2019.

5. P. H. Charlton, M. Villarroel, and F. Salguiero, "Waveform analysis to estimate respiratory rate," in Secondary Analysis of Electronic Health Records, pp. 377–390, Springer, 2016.

Thank You